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Risk Estimation and Stochastic Control of Innovation Processes

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Abstract: *The innovation introduction, no matter whether a product, technology, a method, etc., is being implemented, is connected with considerable risk of investments loss and highly stochastic behaviour, depending on unpredictable factors. It is acknowledged that the innovation passes at least through 6 general stages: 1 – Prestart stage; 2 – Start stage; 3 – Initial expansion stage; 4 – Quick expansion stage; 5 – Stage of reaching liquidity of venture investments; 6 – Stage of project failure and its cancelling. Each state may be refined in details. It is important for the Decision Maker (DM) on one hand to be able to estimate the risk of transitions from a state to state and the probability also for profitable outcome of the initiative – for this purpose a network flow model is proposed; and on the other hand – it is useful if the DM may apply different actions at each stage so that to minimize the losses and maximize the final profit – for this purpose a Markov Decision Process is proposed, which is very closely related to the network flow model and both may be united in a Markov flow.*

Keywords: *Innovation process control, network flows, Markov Decision Process, risk estimation.*

1. Introduction

In contemporary market competition the innovations are of crucial importance for any company or organization for its survival and development. As a rule the innovation processes go ahead with considerable uncertainty and they are too often related to significant risks. Very often venture (risk) funds are invested in them, which rely on significant profits when the project is successfully completed. Of great importance for the venture investors is the control of the current efficiency in the realization of the particular stages of the innovation cycle and the possibility for preliminary (though approximate) calculation of the arising risks and their decrease.

Each innovation, as a rule, goes consecutively through the following seven stages: 1 – Prestart stage; 2 – Start stage; 3 – Initial expansion stage; 4 – Quick expansion stage; 5 – Preparatory stage; 6 – Stage of reaching liquidity, which is a success for the project; and 7 – Failure and cancelling the project [1, 3, 7]. This is the most general scheme for any type of innovation, independent of the concrete subject – a new product, technology, method, etc. The process proceeds in one direction only. It cannot return back to previous stages. If it does, this means in fact a new project. If we imagine the process as a graph structure, this results in a Directed Acyclic Graph (DAG) [4, 5] whose nodes are the states of the innovation process. At each stage a series of activities must be carried out and profound analysis fulfilled depending on the concrete innovation. The first three stages are connected with venture investments and the final – with eventual good profits. It is possible that the outcome is a failure, which is normal for any venture undertaking.

In this paper we propose two models and approaches to risk estimation and control of the innovation processes.

1. A network flow model [4, 6]

This provides the Decision Maker (DM) with a convenient tool which is fairly adequate and ensures reliable data about the risk estimation for the decision.

2. A Markov Decision Process (MDP) model for control of the innovation process [2, 5]

This provides a choice of policies or actions by the DM at each stage, so that maximal profit is gained at the end and the losses are minimized in transitions between states.

Simultaneous usage of both methods may result in quantitative estimation of the Decision Maker's solutions concerning the innovation process.

2. The network flow model

An oriented graph $G(N, U)$ is defined by a set of nodes (states) N and a set of arcs U, connecting the separate nodes (states). The stages, above described, through which any innovation goes, correspond to the set of the nodes N of the graph, and namely

$$N=\{1, 2, 3, 4, 5, 6, 7, 8\},$$

where 1 is the initial state of the decision maker to launch the project and 8 – the final state, where the flow is collected. At that:

$$\Gamma^{1}\{8\} = \text{Ø} \text{ and } \Gamma^{-1}\{1\} = \text{Ø}; \tag{1}$$

where Γ^{1} and Γ^{-1} are the direct and reverse mapping on the graph and Ø denotes an empty set.

Another feature of the graph $G(N, U)$ is that if $i \in N$ and $j \in N$, and $i \le j$, then no path μ_{ij} exists from the node of greater index to the one of lesser index, which implicitly defines a Directed Acyclic Graph (DAG).

A specific feature of the innovation processes is that at transition from a state (node) to a state in the initial three stages, investments are spent, and at transitions in the final four stages in case of success, an increasing profit is achieved, i.e.,

(2)
$$R_{ij} = \begin{cases} \leq 0, \ i \in \{1, 2, 3\}; \\ \geq 0, \ i \in \{4, 5, 6, 7\}; \\ 0 \ \text{otherwise.} \end{cases}$$

The risks, arising at transition from a state to a state play a considerable role in the innovation processes [8]. The most wide-spread approach is the one, in which the risk is considered as a complex function of the product of two measures – the amount or value of the event considered, and the probability that the event has not happened. The first of these measures, corresponding to the transition from state i to state j is denoted by f_{ij} and the second – by P_{ij}, where $P_{ij} \geq 0$ and $0 \leq P_{ij} \leq 1$. In this case the risk at transition from state i to state j is evaluated by the product $f_{ij} P_{ij}$.

If the admissible upper bound of such a risk is denoted by C'_{ij}, then the following may be put down for f_{ij}:

(3)
$$f_{ij} P_{ij} \leq C'_{ij} \ \text{ or } \ f_{ij} \leq \frac{C'_{ij}}{P_{ij}} = C_{ij},$$

(4)
$$f_{ij} \leq C_{ij} \ \text{ for each } \ (i, j) \in U ,$$

where C_{ij} shows the admissible amount f_{ij}, at which the risk does not still exceed the admissible upper bound C'_{ij}.

The innovation process optimal control will correspond to the maximal value of the following objective function:

(5)
$$\sum_{(i,j)\in U} R_{ij} f_{ij} \to \max .$$

If for the realization of the innovation, financing of v units is necessary for the activities, then the optimal distribution of these means will be reduced at the different stages to the following problem of network flow programming: maximization of the objective function from (5), observing inequality (4) and the following two constraints:

(6)
$$\sum_{j\in\Gamma^{1}i} f_{ij} - \sum_{j\in\Gamma^{-1}i} f_{ij} = \begin{cases} v, i = 1; \\ 0, i \neq 1, ..., 8; \\ -v, i = 8; \end{cases}$$

(7)
$$f_{ij} \geq 0 \text{, for each } (i, j) \in U .$$

The network flow model proposed provides a possibility for such control of the innovation process behaviour, by which efficient venture directing of the process is achieved, observing simultaneously that the risk requirements at the separate transitions do not exceed the admissible bounds. The variables introduced in (6) and (7) provide a possibility for innovation process optimization through the following problem of network flow programming:

Maximize the objective function

$$\sum_{(i,j)\in U} R_{ij} f_{ij} \to \max \tag{8}$$

observing constraints (6) and (7).

In the Fig. 1 an exemplary graph for an innovation process is shown. The state numbers are given in squares besides the nodes. The edges are the transitions, the numbers without brackets – the admissible risk, and the numbers in brackets – the optimal values after solving the respective linear programming problem [4, 5]. The dotted line marks the min cut which separates the source and the sink. Node 8 is a fictitious sink just to terminate the flow.

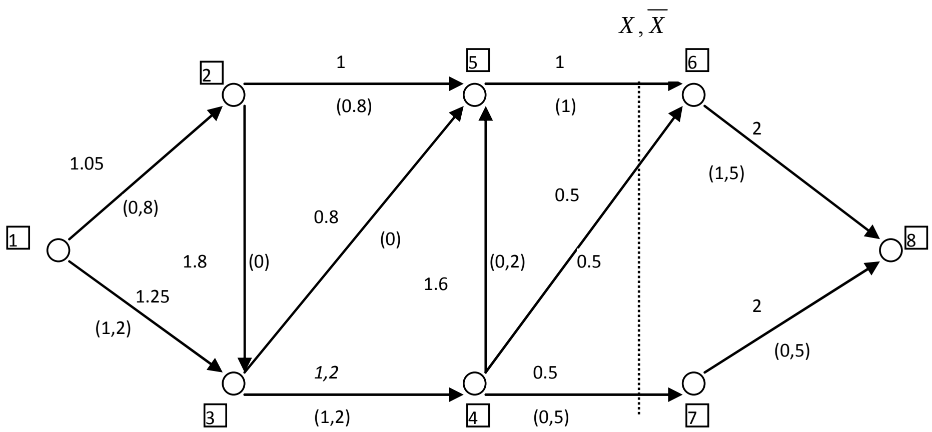

Fig. 1

Table 1 summarizes the source data for the example, including the probabilities.

Table 1

Transition	Admissible risk $\{C'_{ij}\}$	Probability $\{P_{ij}\}$	Upper bound $\{C_{ij}\}$
(1, 2)	0.21	0.2	1.05
(1, 3)	0.25	0.2	1.25
(2, 3)	0.27	0.15	1.8
(2, 5)	0.4	0.4	1
(3, 4)	0.36	0.3	1.2
(3, 5)	0.24	0.3	0.8
(4, 5)	0.32	0.2	1.6
(4, 6)	0.20	0.4	0.5
(4, 7)	0.25	0.5	0.5
(5, 6)	0.15	0.15	1
(6, 8)	0	0	2
(7, 8)	0	0	2

The most important conclusion which may be drawn from the model is:

If parameter v is interpreted as a financial flow, then the maximum possible values, at which the admissible risks at transition from one state to another of the innovation process are not exceeded, must not be greater than v =2 conditional units. Otherwise the admissible risks will be surpassed at some transitions. If a greater value than 2 conditional units is desirable for v, then it is necessary in some manner the risks of the transitions, corresponding to the arcs from the min cut, to be diminished.

3. MDP model for control of the innovation process

We consider an innovation process, which might be at any of the six stages of implementation of a new product. Of course, this is for purposes of methodology. In fact one should begin from the first stage and reach the last one.

We introduce the following denotation: $N_j = \Gamma_j^{-1}$, where the right hand part of the upper equation is a reverse mapping of node j of the graph from Fig. 1. P_{ij}^k denotes the transition probability of the innovation process to pass from state $i \in N$ to state $j \in N$ when using control $k \in K_i$, where K_i is the set of possible policies from state i. As leaping across or going back to stages of the innovation process is impossible, then

$$P_{ij}^k = \begin{cases} \geq 0, i \in N_j;\ j \in N;\ k \in K_i; \\ = 0 \ \text{ otherwise}; \end{cases}$$

$$0 \leq P_{ij}^k \leq 1;\ \sum_{j \in N} P_{ij}^k = 1;\ i \in N;\ k \in K_i.$$

By x_i^k the probability will be denoted that the innovation process falls in state i, when using control $k \in K_i$ from this state.

An important feature of the innovation process is that at transition from one stage to the next one in the first three stages resources are spent, and the transition from one stage to another in the last three stages, an increasing profit is gained, i.e.,

$$r_i^k = \begin{cases} \leq 0;\ i \in \{1, 2, 3\};\ k \in K_i; \\ \geq 0;\ i \in \{4, 5, 6\};\ k \in K_i. \end{cases} \tag{9}$$

Then the maximum restoration of the venture funds initially invested will be obtained at optimal choice of the control actions from each possible state of the process, i.e.,

$$\{k^* \in K_i \mid i \in N_r\}.$$

This optimal control selection from the separate states corresponds to maximization of the objective function

$$\sum_{j \in N} \sum_{k \in K_j} r_j^k x_j^k \to \max. \tag{10}$$

Different methods of linear and dynamic programming [2, 6] may be used to find the optimal solution of the objective function above given with the existing linear probability constraints.

The specific structure of the proposed here multistep discrete Markov decision process corresponds to a sufficient extent to the processes of realization of the innovations and provides possibilities for efficient control of the venture financing of innovations during their realization.

Fig. 2 illustrates a Markov Decision Process for control of the development of an innovation through the six stages. The set of arcs U shows the possible transition from one stage (state) of the innovation process to another one. The denotations on the arcs of the decision graph must be decoded as follows:

$P_{i,j}^{k_l}$ – the probability for transition from stage *i* to stage *j* using control action k_l at state *i*.

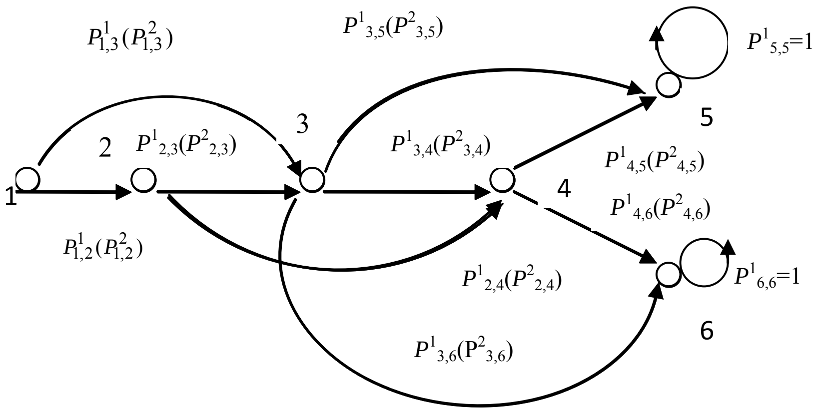

Fig. 2

As a numerical example, the transition probabilities (Table 2) may be used.

Table 2

STATE 1				STATE 2			
Policy 1		Policy 2		Policy 1		Policy 2	
$P^1_{1,2}$	0.8	$P^2_{1,2}$	0.9	$P^1_{2,3}$	0.7	$P^2_{2,3}$	0.8
$P^1_{1,3}$	0.2	$P^2_{1,3}$	0.1	$P^1_{2,4}$	0.3	$P^1_{2,4}$	0.2
STATE 3				STATE 4			
Policy 1		Policy 2		Policy 1		Policy 2	
$P^1_{3,4}$	0.6	$P^2_{3,4}$	0.5	$P^1_{4,5}$	0.8	$P^2_{4,5}$	0.7
$P^1_{3,5}$	0.3	$P^2_{3,5}$	0.3	$P^1_{4,6}$	0.2	$P^2_{4,6}$	0.3
$P^1_{3,6}$	0.1	$P^2_{3,6}$	0.2				
STATE 5				STATE 6			
Policy 1		-		Policy 1		-	
$P^1_{5,5}$	1	-		$P^1_{6,6}$	1	-	

The profits (expenses) $\{r_i^k\}$ have the following values:

$$r_1^1 = -10; r_1^2 = -11; r_2^1 = -5; r_2^2 = -6;$$
$$r_3^1 = 7; r_3^2 = 8; r_4^1 = 10; r_4^2 = 12;$$
$$r_5^1 = 0; r_6^1 = 0.$$

Table 3 shows the optimal policies at each state and the optimal strategy for the innovation process.

Table 3

State $i \in N$	1	2	3	4	5	6
Optimal policy $k^* \in K_i$	1	1	1	2	1	1
Optimal strategy $\{k^* \in K_i \mid i \in N\}$	{1, 1, 1, 2, 1, 1}					

4. Conclusion

The innovation processes are as a rule connected with significant risk and investments of venture capital. Two approaches are offered for risk estimation and optimal control at each step of the process – network flow analysis and Markov decision processes control. It is important that a profound analysis is carried out at each step of the processes and appropriate actions to be performed for the successful outcome of the innovation. The results connected with the network flow interpretation of the innovation process allow some conclusions to be inferred about this process:

If parameter v is interpreted as a financial flow, then the maximum possible values, at which the admissible risks at transition from one state to another of the innovation process are not exceeded, must not be greater than a given value.

The method proposed in the present work for using multistep Markov decision processes for description of the innovation processes provides a possibility their stochastic character to be recognized to a considerable degree and an efficient procedure to be proposed for their behaviour control.

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