A SIMULATION BASED APPROACH FOR THE EVALUATION OF OUTCOME DRIVEN INNOVATION MODELS

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KEYWORDS

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ABSTRACT

The evaluation of the opportunity of investments on complex production processes is a critical factor in order to enable the balance of risks and potential benefits. There is no out-of-the-box tool that can solve this problem: only the experience of the responsible expert and his knowledgeability of the process can help. Outcome Driven Innovation is an evaluation technique that can support decisions, based on a structured approach to process analysis and on the availability of domain experts: anyway, the need for experts can make the evaluation itself very expensive. In this paper a simulative approach is used to provide an a priori characterization of the conditions that can suggest the opportunity of adopting Outcome Driven Innovation for a process.

I. INTRODUCTION

In 1980 business leaders began to recognize that being technology driven was just not good enough. Up until that point it was common for companies to create a new technology and then attempt to find a market in which the technology could flourish. Traditional Research and Development laboratories such as AT&T or Motorola R&D tried to build a mass market business for products based on a new technology that appealed only to a narrow market. With a failure rate approaching 90%, R&D expenditures under scrutiny and lead-times for success averaging nearly eight years in ICT industry USA, it was clear that a new approach was needed [1]. Companies began to adopt the ideas and principles associated with the customer driven approach, i.e., first understand what the targeted customers' need and want, and then invest in the creation of a new product or service. Indeed, over the past two decades, the customer driven approach has become the mantra for all organizations and for innovation in particular. But after twenty years of customer driven thinking U.S. companies still find that 50 to 90 percent of their product and service initiatives are failures [1]. A big issue in the customer driven approach regards the fact that customers express their requirements in a language that is convenient for them, which often, however, is inappropriate for creating innovation.

Creating innovation becomes an uncertain practice [2] surrounded by accidental events, intuition and experience of individuals, heavy dose of serendipity and unconventional practices, none of which is necessarily relevant. According to the growing importance of innovation, the strategic role of a methodology able to help entrepreneurs and innovators to set up an innovative process was required: the outcome methodology has been considered as alternative methodology for fostering innovation [1].

Unfortunately, no out-of-the-box methodology can provide the silver bullet to ensure success. Outcome Driven Innovation (ODI) [3] is a valuable support for decisions, widely assessed and adopted, but the need for experts and the need for a non negligible time amount for the evaluation of the stages of the process can make the evaluation itself very expensive. Consequently, a set of thumb rules that can suggest a priori what are the characteristics of a process that is more likely to maximize the success chances in the application of the methodology, which parameters are significant for success and how they influence it would be a useful tool to increase control on the risk.

In this paper a simulative approach is adopted to shape out the type of processes and the characterization of the conditions that can assist the decisions about the opportunity of adopting Outcome Driven Innovation for a process.

The use of simulation is widely adopted in the field of production and management (see e.g. [4]), but in this case we simulate the behavior of the panel of experts that are in charge of judging over the outcomes of the various phases in which a process is organized, and the criteria according to

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which a decision maker that is applying ODI will operate.

In order to (partially) explore the set of the possible processes to which ODI could be applied, a probabilistic approach has been chosen to generate the set by varying some of the parameters of each phase of the process (see e.g. [5]). The fixed structure of the process in the ODI view organizes it into eight phases, each of which produces a variable number of outcomes: in this approach, the average number of outcomes per phase is considered as a free variable of the model, that is set by the model user according to empirical considerations over the domain of the process. The number of outcomes per phase is defined as a stochastic variable, to simulate the actual variability emerging in real processes phase by phase.

The evaluation of each outcome by a panel of experts is simulated by two stochastic variables: the importance of the outcome and the satisfaction about the outcome. For each of the two variables, the variance is used as a simulation parameter, to understand how sensitive the overall ODI application is with respect to the dispersion of importance and satisfaction on the set of processes. Moreover, also the correlation between importance and satisfaction is a simulation parameter, as in real processes the two can be more or less interrelated, to evaluate the impact of its spread in the set of processes. Another parameter is given by the innovation threshold, that is used to decide whether, according to innovation and satisfaction, an outcome is to be considered innovative, thus worth of investments, or not.

The paper is organized as follows: in Section II a general introduction to ODI is provided; in Section III the simulation approach is presented; in Section IV a case study is proposed; conclusions and future works follow.

II. OUTCOME DRIVEN INNOVATION

A way to predict more theoretically the value created has been found redefining the market concept based on the job to be done theory. The theory builds on two very simple concepts: customers hire product and services to get a job (the job is the stable unit of analysis [2] [1]), and the consequential observation that customers will adopt products and services that help them get the job done better [2] [1], and to get the whole job done on a single platform [1].

To systematically uncover more innovation ideas Bettencourt and Ulwick [6] create job mapping: breaking down a job that customers want done into discrete steps, then brainstorm ways to make steps easier faster or unnecessary.

All the jobs have the same eight steps (see Fig. 1 from [3]) that are summarized as follow:

1) Define: determinate customers goals and plan resources;
2) Locate: gather items and information needed to do the job;
3) Prepare: set up the environment to do the job;
4) Confirm: verify that customers are ready to perform the job;
5) Execute: carry out the job;
6) Monitor: assess whether the job is being successfully executed;
7) Modify: make alterations to improve execution;
8) Conclude: finish the job or prepare to repeat it.

To get to the next step, it has been postulated that customers use well defined metrics to assess how good the job is done [1]. Consequently, an approach has been implemented to capture such metrics and to measure them on a representative sample of the market [1] obtaining an objective and quantitative assessment of market opportunities, in terms of where value can be created.

As each of the metrics addresses one individual element of dissatisfaction, i.e. one aspect of the job execution that customers are still struggling to achieve, they make possible to objectively rate each solution by its ability to better satisfy these aspects. That ability is now a measured element of value creation.

The job to be done theory, extended with outcome methodology (the metrics the costumers use to evaluate the job execution), provides tools to identify (all the) individual elements of dissatisfaction in the execution of a job, and so to assess how a new solution (innovation) rates in term of improving satisfaction with these elements. This is a value creation assessment.

In the specific the outcome or metrics belong to 3 different types:

- Speed metrics: getting the job done faster;
- Stability metrics: eliminating variability on the job;
- Output metric: improve the output of the job.

Outcome drive innovation framework is structured around the link between opportunity for innovation and need not well satisfied. Identifying an opportunity of undeserved needs means find a specific job/activities a customers need to exploit. Needs are strategically linked to customers activities (or job to be done) and their importance and satisfactions. Best Opportunity for innovation creation is when need is very important for a customer and it is not satisfied by market products or services.

Using this formula, the needs that are most important and least satisfied receive the highest priority:

$$Opportunity = Importance + max(Importance - Satisfaction, 0) \tag{1}$$

If this link exist is possible to develop an innovation with a considerable value for the customer target and a potentially market growth for the organisation.

III. SIMULATION APPROACH

This section provides the description of the simulator we implemented to analyze the applicability of ODI over a set of different possible scenarios. The proposed framework is based on probabilistic approach in order to generate different sets of parameters that define each phase of the process. The entities that characterize the real model are described by stochastic variables. To present our work we generate these values by selecting a possible set of distributions, but it is important to note that different choices can be performed in order to exploit the simulator for describing different real system configurations. We implemented it in GNU Octave [7].

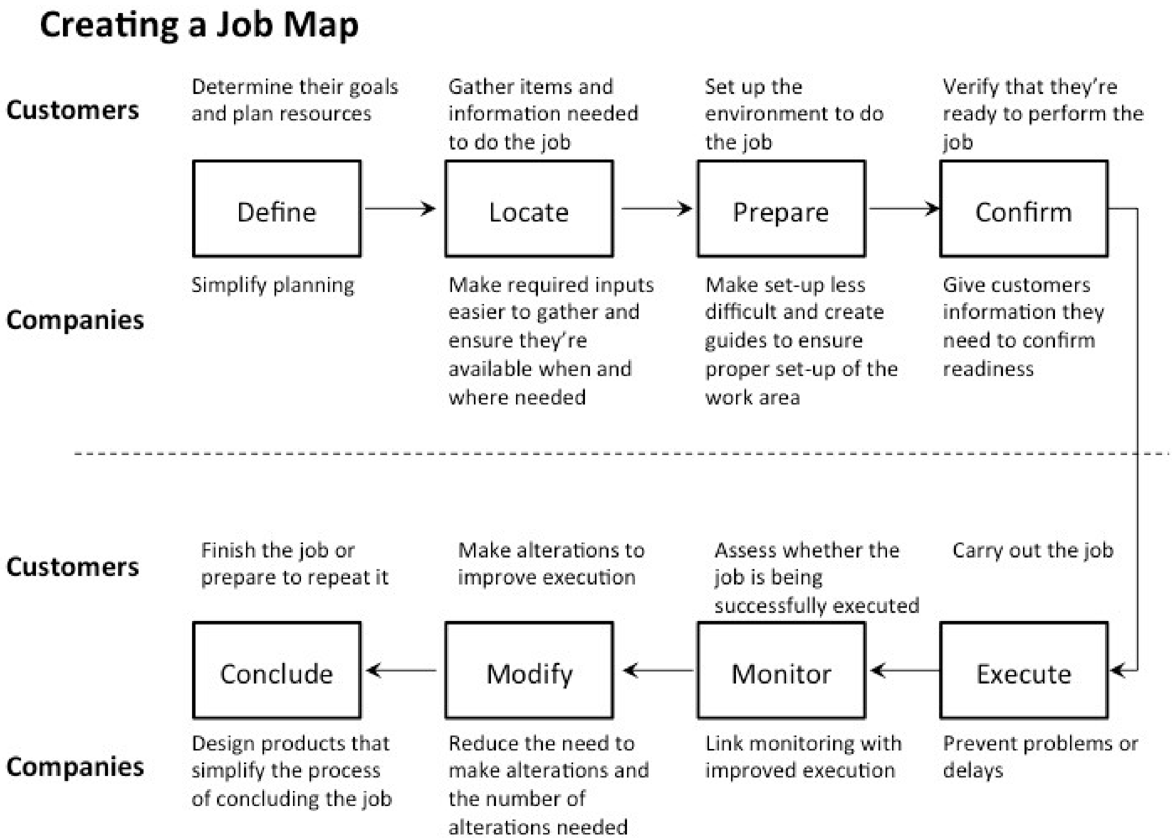


Fig. 1. The eight phases

A. *The Outcomes*

The number of outcomes for each phase of the process is a stochastic number generated with a probability distribution. In this case study, we set a Poisson distribution whose parameter n (mean) is derived for each phase by a Zipf distribution. In particular, the number is randomly generated with a parameter that is function of the number of phase it belongs. In this way, we assume that, according to the phase, the simulator can produce a different number of outcomes, and the use of a Zipf allows us to set the first phases with a potential higher number of outcomes. The Zipf parameter is denoted with Θ. Different policies can be modelled by other distributions or functions.

Once the number of outcomes is generated for each phase, the simulator can spread it with a given probability in three different categories: speed, stability, and output. We set the probability that the outcomes are assigned to a given category as a Zipf Distribution with parameter Θ. In this case the choice aims to account for a category ranking where we set the speed as the most probable, the stability as the second, and the output as last (details are reported in the next Section). Other options can also be implemented by setting different probability distributions.

B. *Importance and Satisfaction*

The evaluation of each outcome is simulated by two stochastic variables: the importance of the outcome and the satisfaction about the outcome. For each phase and for each outcome category a different probability distribution is used to define both importance and satisfaction parameters.

In this case study, the simulator generates the importance and satisfaction elements for all the outcomes by a Truncate Bivariate Normal distribution. The related parameters μ and cv (mean and variance) are defined by Zipf distribution to keep the following criteria: the outcomes of phases with higher number of outcomes have higher satisfaction parameters, whereas the outcome belonging to categories with lower probability to be assigned to have higher importance parameter. The choice of a Bivariate Normal distribution allows also to set the correlation parameter ρ to keep into account that in real processes importance and satisfaction can be more or less interrelated. We would remark again that the simulator can generate the outcome importance and satisfaction parameters with any other probability distribution for describing different scenario and criteria.

C. Innovation and Opportunity

The simulator first generates the number of outcomes for each phase, then it assigns them to the categories, and finally it produces the importance and satisfaction parameters for any of them. After that, it computes the Opportunity Algorithm (see Section II, equation 1) by using the previous results for all the outcomes in order to evaluate their innovation level. To decide whether, according to importance and satisfaction, an outcome is to be considered innovative, thus worth of investments, or not, a parameter called Innovation Threshold (denoted with T) is set. The simulator selects only the outcomes whose innovation evaluation provided by that Opportunity Algorithm is equal or higher than the threshold. Furthermore, another parameter called Innovation Probability Factor (denoted with p) determines the probability that an outcome with a value equal or higher to the Innovation Threshold has to be successful. The simulator uses this parameter to provide the set of outcomes that can produce innovation and that are also successful.

IV. A CASE STUDY

To show the effectiveness of the simulation, we proceed to the generation of several sets of simulated traces for processes with given sets of parameters and then we analyze the characteristics of the various outcomes, to obtain a global idea of their behavior. Figure 2a shows an example of a trace produced during one simulation run. In particular, in this case, the simulation has generated 124 outcomes of the three different types in the eight phases. For each outcome the importance and satisfaction values have been generated. Using the provided threshold $T = 15$, 7 opportunities for innovation have been selected and for each of them a success probability has been assigned, as shown in Figure 2b. Different runs, with different seeds, will produce different traces: Figure 2c shows the number of outcomes generated in the eight phases for three different runs.

Simulation requires the computation of confidence intervals. In this work we focus on the evaluation of distributions, for which the computation of confidence intervals is not a simple issue and can be considered a research topic on its own. To verify the accuracy of our results, we have divided the metrics computed by the simulator into bins, and considered the probability of belonging to a bin as a Bernoulli trial. In particular we have counted, out of N repetitions, the number of runs n in which the value of the considered performance index was contained in a given bin. We then applied the Wald interval estimation [8] to compute the 95% confidence intervals of the probability parameter p of a Bernoulli distribution with N trials out of which n are successful. As an example, let us focus on the distribution of the opportunity value: since it is a numerical value in the range $[0, 20]$, we have divided the statistics into 100 bins of size 0.2 each and computed both the cumulative distribution function (CDF) and the probability distribution function (PDF). Figure 3 shows that for the CDF, a small number of simulations is enough to produce smooth results. When considering however the PDF, as in Figure 4, a larger number of runs its required to obtain smooth results since the considered performance index belongs to a bin in a smaller number of simulation. In our experiment we will fix $N = 10000$ runs to consider a tradeoff between accuracy of the results and simulation time. Experiments were run on a standard laptop and required less than ten minutes each. To simplify the presentation, only the center of the confidence intervals will be shown in the following.

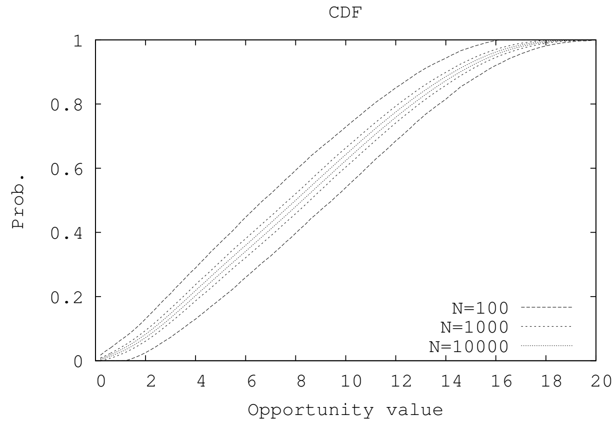


Fig. 3. Confidence intervals for the cumulative distribution function of the opportunity value.

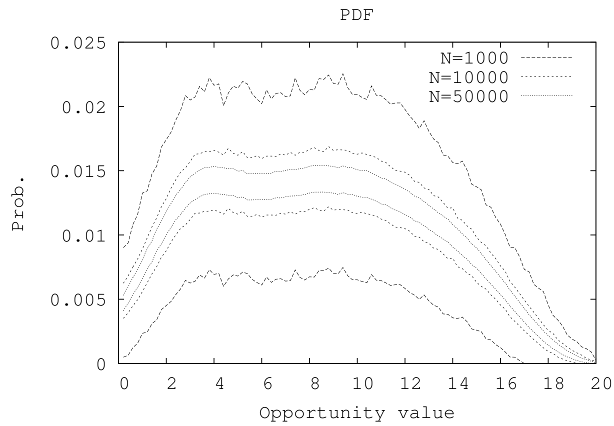


Fig. 4. Confidence intervals for the probability distribution function of the opportunity value.

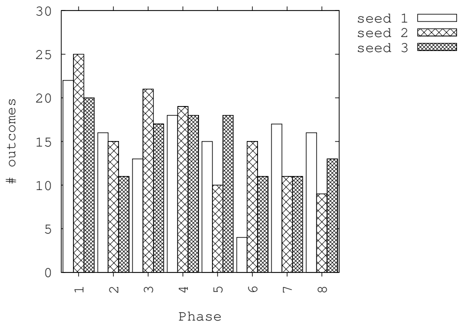
We start studying the distribution of the opportunity value for different scenarios to characterize the effect of the variance and of the correlation between the importance and the satisfaction levels of the outcomes. Figure 5 shows the results. Positive correlation (Figure 5c) implies that the more an outcome is important, the more it is also satisfied leading to a low opportunity. This can be seen by the lighter tail that the distribution has. It is instead interesting to note that when there is a negative correlation (Figure 5b), indeed more important outcomes are also characterized by a low satisfaction level as seen in the right tail of the distribution. However, there is also an increase in the probability of having very low opportunity values as a consequence of the way in which the algorithm

N.	Phase	Type	Importance	Satisfacion
1	1	Stability	3,64	5,03
2	1	Speed	3,70	4,07
3	1	Speed	1,73	2,44
20	2	Stability	6,35	6,33
21	2	Speed	7,68	0,70
22	2	Output	9,33	3,44
123	8	Stability	7,29	0,04
124	8	Speed	0,03	3,91

a)

N.	Phase	Type	Importance	Satisfacion	Opportunity	Success
76	4	Output	9,58	1,82	17,35	0,615
111	7	Output	9,36	1,54	17,19	0,598
47	3	Stability	9,32	1,97	16,66	0,543
91	5	Stability	9,98	3,70	16,27	0,505
102	6	Output	8,59	1,06	16,12	0,492
33	2	Speed	9,16	2,93	15,38	0,429
22	2	Output	9,33	3,44	15,23	0,417

b)



c)

Fig. 2. Simulation traces: a) outcomes , b) opportunities, c) number of opportunities per phase in three different traces.

works. Variance does not play an important role for negative correlations, but its effect is more visible when $\rho = 0.8$: in the former case larger variances create more uniform distributions for smaller opportunity levels.

The previous scenario leads also to a different distribution in the number of opportunities that will be considered for possible innovations. This is shown in Figure 6, where it is clear that the center of the distribution moves toward higher values as the correlation among the inputs turns from positive to negative. It is interesting to note how, when the correlation is negative, a higher variance produces worse results, while when $\rho > 0$ a higher variance improves the situation.

The number of outcomes in the different phases and the types of innovations proposed play a role in the distribution of the opportunity value. In our model, we have determined this parameters using two Zipf distributions. Figure 7a shows how the number of outcome can be divided per phase under three different parameterization ($\theta = 0.5$, $\theta = 0.7$ and $\theta = 1$), and Figure 7b focuses on how the outcome are categorized according to the three different types. Then, Figure 7c shows the effects of these distributions on the different shapes of the opportunity value. As it can be seen, when a scenario has a more uniform distribution of outcomes and outcome types, it has a larger probability of having opportunity values above the threshold.

One of the key features of the simulative approach is the ability to study the considered scenarios in depth by allowing to capture complex performance measures. For example, Figure 8 shows how different thresholds for the opportunity level, and the probabilities of success for outcomes at the threshold, affect the joint distributions of the number of selected outcomes and number of successes. The more a plot is centered across the 45° line, the more likely an innovation is likely to be successful. The more a plot is shifted away from the origin, the more the scenario will be able to produce innovations. The more the plot is packed near a point, the lower will be the uncertainty in the number and the success of the considered innovations. For example, the scenario in Figure 8a shows a large possibility of successful innovations, but with a larger uncertainty, while Figure 8c describes a case where less innovations are possible, but their success is more probable.

From the joint distributions, marginal values such as the probability of successful outcomes can be computed, as shown in Figure 9. From this we can see that by lowering the threshold we can increase the number of successes for any value of p. However, if we consider that innovations that are not successful might incur in extra costs, situation might be different, as shown in Figure 10. In particular we have computed the average cost / benefit β of a scenario as:

$$\beta = \sum_k \sum_s p_{sk} \left[s\lambda - (k-s)\mu \right]$$

where k is the sum over the outcomes, s the sum of the successes, π_{sk} the joint probability of having s success out of k outcomes, λ is the benefit obtained from a successful innovation, and μ is the cost incurred from an unsuccessful opportunity. For example for a gain $\lambda = 7$Keuro and a penalty of $\mu = 10$Keuro, as in Figure 10, we can see that for risky scenarios characterized by a small probability p of success at the threshold, it is better to set a higher threshold to reduce the loss.

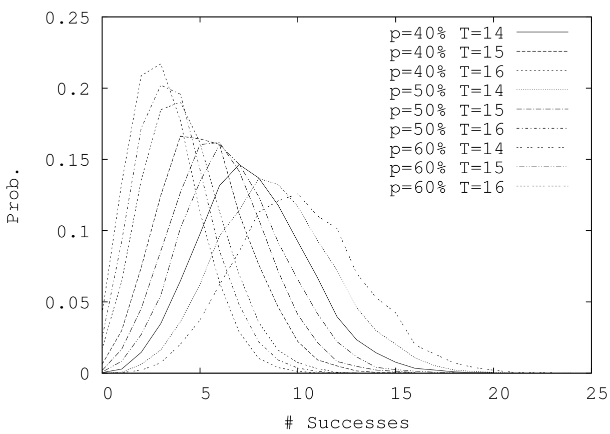
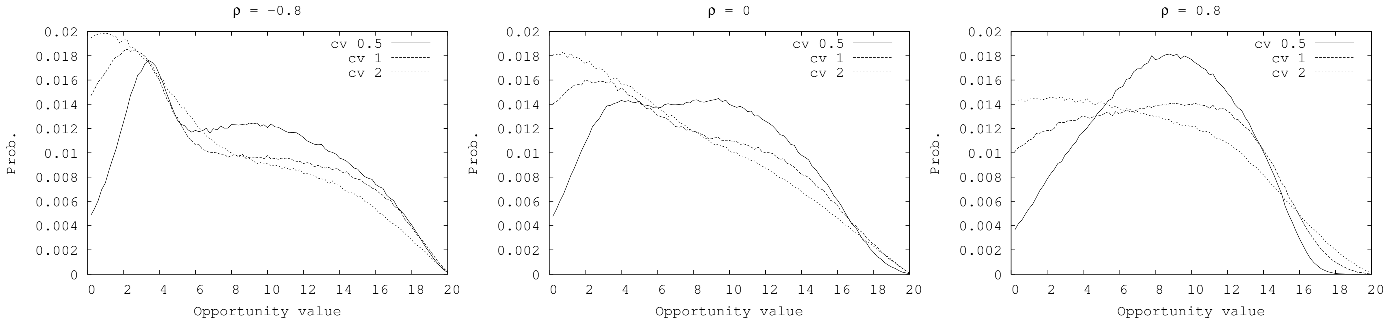


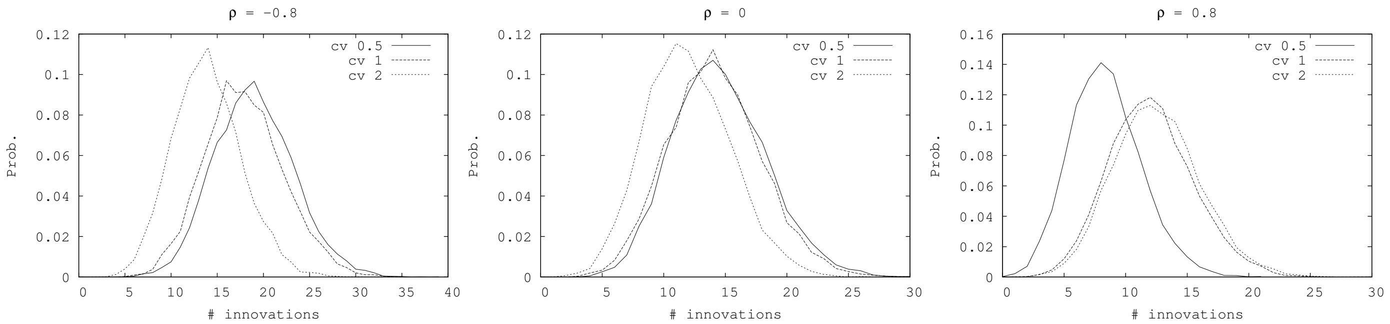
Fig. 9. Distributions of the number of successes for different thresholds and probabilities of success for outcomes at the threshold.

Finally, Figure 11 shows the distribution of the percentage of successes for the cases whose parameters are given in Table



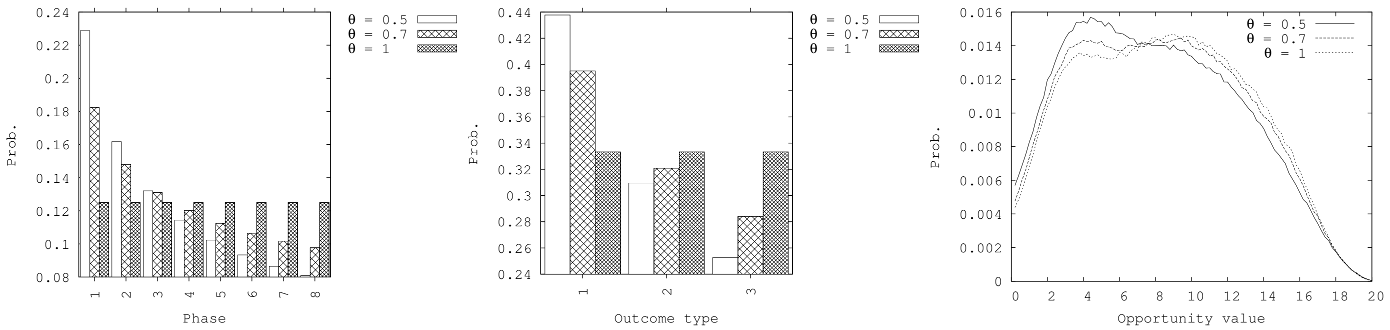
a) b) c)

Fig. 5. Probability distribution of the opportunity value for different correlation and variances of the satisfaction and importance levels: a) $\rho = -0.8$, b) $\rho = 0$, c) $\rho = 0.8$.



a) b) c)

Fig. 6. Probability distribution of the number of outcomes considered for possible innovation for different correlation and variances of the satisfaction and importance levels: a) $\rho = -0.8$, b) $\rho = 0$, c) $\rho = 0.8$.



a) b) c)

Fig. 7. Probability distribution of the opportunity value for different parameters θ of the Zipf distributions: a) Distributions of the outcome in each phase, b) Distribution of outcome types, c) distribution of the opportunity value.

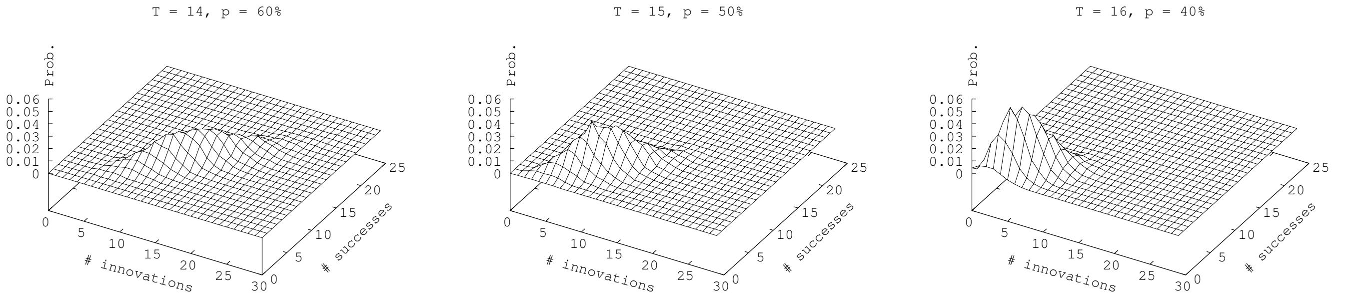
I. In scenarios with parameters like the one in B, there is a high probability of having a 100% of successes among all the innovations that have been considered: this is mainly due to the fact that even innovations at the threshold have a very large success probability. Case A is instead the worse, since it has a much smaller success probability, even at a lower threshold. When the scenario has a negative correlation (Case C), the percentage of successes tends to be more packed around a given value. Positive correlation (Case D) instead produces a larger variance in the percentage of successes.

TABLE I
PARAMETERS FOR THE CASES CONSIDERED IN FIGURE 11

Case	cv	ρ	T	p	n	θ
A	1	0	15	40%	120	0.7
B	1	0	16	60%	120	0.7
C	2	-0.8	14	50%	120	0.7
D	0.5	0.8	14	50%	120	0.7

V. CONCLUSIONS AND FUTURE WORKS

In this paper we explored a simulation approach for the evaluation of the effectiveness of ODI in dependency of some



a) b) c)

Fig. 8. Joint distributions of the number of selected outcomes and number of successes for different different thresholds and probabilities of success for outcomes at the threshold: a) $T = 14$, $p = 0.6$, b) $T = 15$, $p = 0.5$, c) $T = 16$, $p = 0.4$.

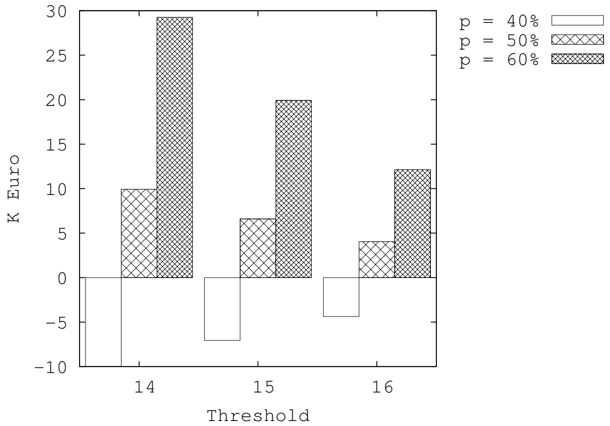


Fig. 10. Cost / Benefit for different thresholds and probabilities of success for outcomes at the threshold.

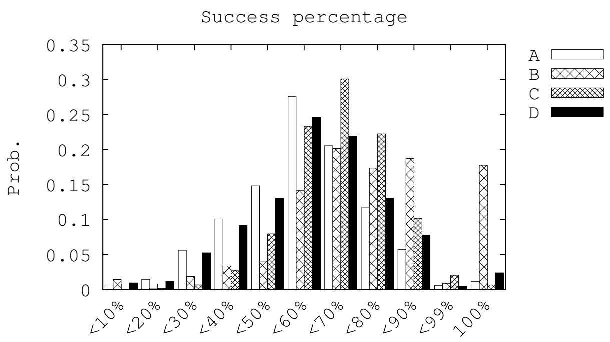


Fig. 11. Distributions of the percentage of success for the case defined in Table I.

characteristics of the processes to which resources are planned to be invested. The simulated scenarios show some interesting hint to support experts in the application of the technique to real cases.

Future works include the definition of a dedicated modeling language to describe ODI models in a multiformalism framework such as SIMTHESys [9] [10] or OsMoSys [11] [12] to integrate the evaluation in more complex and articulated scenarios including the nature and the performances of processes in composite metrics.

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