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X-Efficiency of Innovation Processes: Evaluation Based on Data Envelopment Analysis

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X-Efficiency of Innovation Processes: Evaluation Based on Data Envelopment Analysis

The Case of SMEs in Normandy, France

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Abstract Innovation in small and medium-sized enterprises (SMEs) is a source of regional development and enables enterprises to improve their competitiveness. However, the intensification of innovation effort depends upon a better understanding of the innovation process, in particular the assessment of its innovation capacity to process its resources and various activities in efficient manner into better results. This paper deals with innovation process modeling and innovation measurement, in order to provide answers to these recurrent questions of the entrepreneurs in these SMEs. Thus, first we propose a model of innovation process as a collective design process that involves the interplay of two categories of activities, such as exploratory activities and value oriented activities, centered on the entrepreneur. Then from this model, we evaluate: (a) the innovation capacity from the process activities and too the outputs of innovation process; (b) the X-(in)efficiency using multiobjective (MOLP) data envelopment analysis (DEA) model of innovation processes. Through MOLP-DEA method, we decompose the X-inefficiency in technical inefficiency and congestion to highlighting the miss-use or the under-utilization of innovation capacity, as resources of process. Finally we measure X-inefficiency by an overall index taking into account of all aspects of inefficiency as the enhanced DEA Russell graph efficiency measure. For the empirical analysis, we use the data from a representative random sample formed by 80 innovative enterprises of regional SMEs of Normandy in France. The results show that most of innovation processes are X-inefficient in SMEs of Normandy. This X-inefficiency is more characterized by the congestion problem than the technical inefficiency. That shows the difficulties of some entrepreneurs to implement the rules and standards of interplay between some activities.

Keywords Innovation Process · X-Efficiency · Multiobjective Linear Programming · Data Envelopment Analysis · Russell measure.

1 Introduction

Theoretical and empirical works on innovation and business have focused on two fundamental points regarding innovation: the role of small and medium enterprises (SMEs), and the influence of organization (Cohen, 1995; Rothwell and Dodgson, 2004; Forsman, 2011). Innovation is also a challenge for any strategy of regional development based primarily on the strength of local SMEs (Feldman and Florida, 1994). According to the survey of IDEIS project[1], the majority of entrepreneurs feel that they do not innovate sufficiently. For most of them, the innovation process is more or less a black box.

This paper addresses the unsatisfactory development of business innovation due to inefficiencies in the innovation process. These inefficiencies lead to difficulties for an entrepreneur seeking to model the innovation process, and attempting to identify and to measure the dimensions of innovation, such as, the inputs, the capacity, the outputs, and the efficiency.

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[1] The IDEIS project (`https://www.unicaen.fr/mrsh/projetideis/`) focuses on innovation capacity of SMEs. It is part of the Government-Region Project Contract (2007-2013) and benefits the European Regional Development Fund. The IDEIS survey (2009-2010) includes a representative sample (random, stratified) of SMEs in Normandy, France.

In fact, one of these difficulties derives from those aspects of innovation that are not directly measurable or observable or even intangible (Hansen, 2001; Guan et al, 2006). However, the literature about the subject provides some proposals of audit tools based on observable indicators to enable decision makers to collect data on innovation (Chiesa et al, 1996; Dodgson and Hinze, 2000; Hansen, 2001; Grupp and Maital, 2001). About the same topic, the Organization for Economic Cooperation and Development (OECD) has elaborated some guidelines for the collection of data on innovation in the Oslo Manual (OECD, 2005), which is widely used in the Community Innovation Surveys (CIS)[2]. This manual covers all the appropriate information on activities, and the actual outcomes of the innovation process. It also clearly distinguishes inputs from outputs in the process. The construction of our survey support was based on the principles in this manual (Gaussens and Houzet, 2009). According to Oslo Manual, we consider innovation as the implementation of a new or significantly improved product, or process, a new marketing method, or a new organizational method in business practice, workplace organization or external relations in our investigation.

Moreover, the innovation process is a multidimensional and complex organization with multi-inputs in activities and multi-outputs in value creation (Hansen, 2001; Guan et al, 2006). Its involves various activities, which involve financial, material and immaterial resources. Here, we rather focus the analysis on the activities which are coordinated and oriented by the entrepreneur than the use of economical resources. This is the capacity that enables the business to achieve the value creation. In fact in line with Amit and Schoemaker (1993), the innovation capacity of an enterprise is considered as the ability to deploy its resources through the activities that make up the innovation process: design, organizational learning, knowledge and creativity activities. As outlined in Forsman (2011), this approach is ideal for SMEs since the innovation process is more a collective design process through all the activities of the enterprise than a well-defined process based on dedicated resources, such as formal R&D, and deploying as part of a strategy. Therefore we deal with the *X-efficiency* of an organization due to Leibenstein (1966, 1969, 1977). On the assessment of the X-efficiency, the use of parametric methods is not appropriate in this case for two reasons: first these methods require a good specification of functional form and distribution of production random, secondly they need to aggregate all output dimensions. Guan et al (2006) and Leibenstein and Maital (1992) have proposed the use of data envelopment analysis (DEA) to analyze the X-efficiency of an organization. In this paper, we employ the DEA method to evaluate the components of X-efficiency of innovation processes. Besides, due to lack of information on the nature of technology innovation, DEA method is used under variable return to scale (VRS) to estimate the empirical production frontier. Then we use the enhanced DEA Russell graph efficiency measure to aggregate all dimensions of X-efficiency in order to assess the magnitude of X-inefficiency.

In addition we consider two outputs of the innovation process: innovation intensity (cf. section 4.1), and total factor productivity (TFP). In our framework, innovation intensity takes into account the different types of innovation[3] that can be achieved in an enterprise. Its measures the diversity of innovation. TFP measures how far this particular enterprise makes use of its resources. This suggests that a priori these two indicators have each the same importance in the objective function for the decision maker: they measure the same phenomenon. In the other words, the innovation made in the enterprise, the first through innovation achievements of the enterprise; the second, as the monetary translation of the significant improvements that have been introduced in a particular field of business[4].

However, the evolvement of outputs depends on the market structures which determine innovation strategy of the enterprise. We assume therefore that the two outputs are not necessarily and directly related. For instance, an enterprise can adopt a niche strategy and achieve a breakthrough innovation in one area; but then we can observe a rather low level of innovation intensity, coupled with relatively strong TFP. By contrast, a business in a highly competitive environment may be forced to make minor innovations in many areas just to survive or maintain its TFP. In this situation, we can observe a high level of innovation intensity. Thus the radial measure is not appropriate for our study (Guan et al, 2006). We have chosen instead a multiobjective DEA (MOLP-DEA) model to evaluate the X-efficiency of innovation processes.

This paper is organized as follows. In section 2 we provide a model of the innovation process as a design process. Next in the same section, we define and describe the X-efficiency and its components. In section 3, we propose an evaluation of individual X-efficiency in the innovation process and an identification of internal sources of its inefficiency from MOLP-DEA. Before the conclusion, in section 4, we realize an

[2] cf. `http://epp.eurostat.ec.europa.eu/portal/page/portal/microdata/cis`.

[3] The distinctions of different types of innovation are taken from the Oslo Manual: innovation product, process, organization and marketing.

[4] An enterprise is considered innovative if it introduced at least one type of innovation (product, process, marketing or organization) from 2006 to 2008 (Gaussens and Houzet, 2009).

empirical analysis on the case of innovation processes of the SMEs of the region of Normandy in France from data of IDEIS project survey.

2 X-Efficiency of innovation process

First, the innovation process transforms strategic, technological and non technological knowledge specific of the entrepreneur into business process which can be achieved without completely knowing it, i.e. converges to the new value (Chesbrough and Rosenbloom, 2002) without certainty. In the other hand, taking note of the work of March (1991); Kline and Rosenberg (1986); Nooteboom (2001); Hatchuel and Weil (2009); Le Masson et al (2011), this innovation process is considered here as a process of innovative design, characterized by interplays between *value oriented* or *problem solving / solution focused* activities, and *explorer oriented* activities. We consider design activities oriented to the definition of value, and organizational learning activities oriented to the collective capacity to realize value. The knowledge activities and creative activities are exploratory to the extent that they allow the value oriented activities to explore potential value and to orient themselves towards innovation. The question then is whether the insufficient development of innovation in SMEs is related:

(a) To a lack of innovation capacity defined previously as a lack of activities constituting the process innovation, reflecting a problem of resources allocation. Indeed we can observe some complementary activities in the innovation process, for instance when internal knowledge is not enough the entrepreneur needs to access to external knowledge. In that case, the entrepreneur needs simply to increase the capacity of innovation process of its business (cf. Fig 2).

(b) Or the opposite to miss-use or under-utilization innovation capacity, reflecting in this case a form of X-inefficiency of the innovation process (cf. Fig 2). We are instead interested on this question.

The X-efficiency of an innovation process is thus based on the contribution of explorer oriented activities to innovation activities, and on the innovative content of the value oriented activities. Also, this X-efficiency depends more on interplays between the activities than on a simple balance between them. Finally, if we measure innovation as the outcome of the innovation process using innovation intensity and the total factor productivity, the innovation process can be represented as in Fig 1.

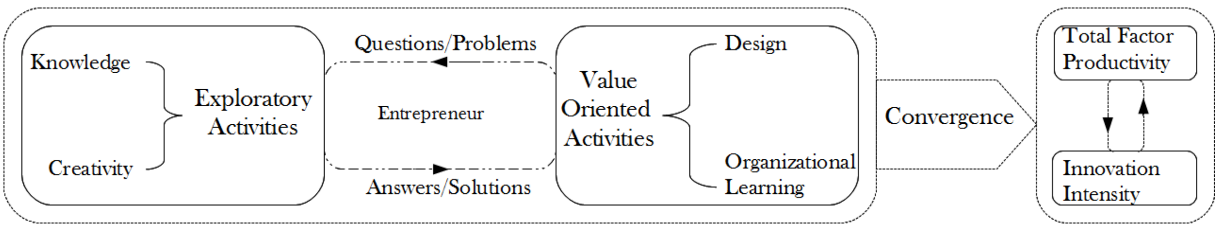

Fig. 1 Innovation process as collective design process.

In addition, we also define the innovation process as a network of activities centered on the entrepreneur whose in-efficiency is X-in-efficiency according to Leibenstein (1966, 1969, 1977). The X-efficiency means here the optimal use of the rules and standards of interplays[5] between individuals in the organization within which the process of collective design is developed with the necessary and sufficient innovation capacity. This process generates a co-construction of collective activity based on a continued expansion of questions from value-oriented activities and possible solutions from exploratory activities. They are the bearers of value concepts that guide responses (Hatchuel and Weil, 2009; Le Masson et al, 2011). Therefore X-inefficiency in the innovation process of an enterprise can be decomposed into technical inefficiency and congestion (Leibenstein, 1966, 1969, 1977). In the next two sections, we describe meaning difference between the latter.

2.1 Technical inefficiency of innovation process

Here, we are interested on output technical in-efficiency since the aim is to gain the best return with optimal innovation capacity from the process activities. Technical inefficiency means relatively a less

[5] The possibility of interplays between individuals requires that they have relations, which is based on communication, coordination and cooperation rules and media, such as the possibility of unexpected conversations, contracts and agreements, a shared language, a common knowledge base ...

efficient implementation of rules and standards of interplays in the collective design process. In the other words, that results from the technical failure of interplays in the innovation process of its business, despite the existence of rules and standards. That often appears in the form of miss-orientation of process activities or of miss-adaption of the optimal pace of individual activities. Both cases can cause the loss of equilibrium between process activities. Then that can prevent to attain the best productivity or innovation intensity level. Indeed, this situation can reduce for instance the production pace, during the adjustment time to the best technique, despite the innovation capacity that represent its activities. In that case, the entrepreneur needs simply to improve the interplay techniques, keeping the same innovation capacity of its business, in order to remove this form of X-inefficiency (cf. Fig 2).

The technical inefficiency is measured by the distance η (y in Fig 2) between the output of the enterprise under evaluation (at point M in Fig 2), and an observable enterprise achieving the maximum technically feasible output with the same innovation capacity (at point C in Fig 2).

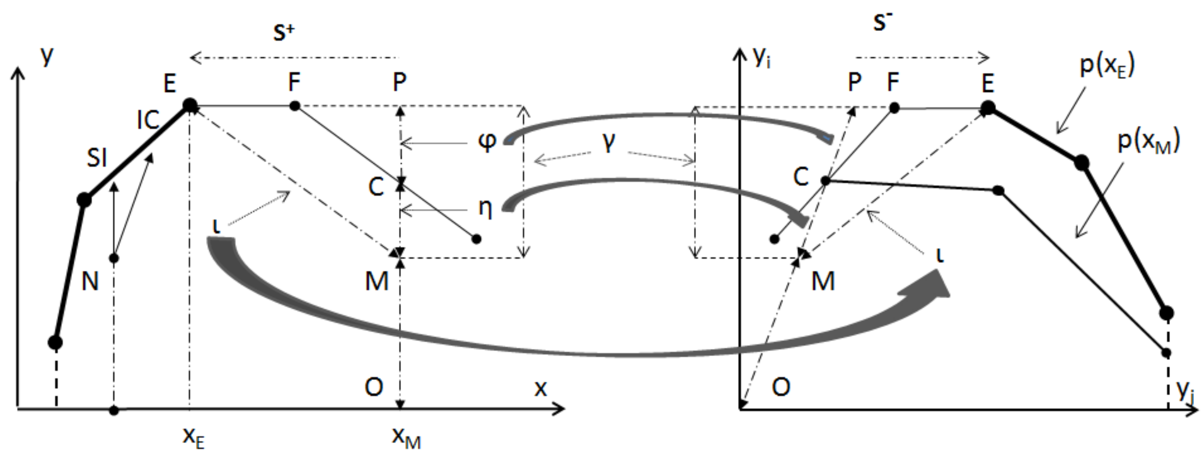

Fig. 2 Illustration of X-Efficiency. $p(x_E)$ is the set of possible new values with the innovation capacity x_E. $N \to SI$ means a simple technical improvement, $N \to IC$ means the need to increase the capacity. In right, $p(x_E)$ is mathematically a cutting of the efficient frontier at x_E.

2.2 Congestion in innovation process

Congestion problem results from the inability of the entrepreneur to managing the innovation process. This inability results to the non-implementation due to the lack of efficient rules or standards of interplays in certain areas of the collective design of its business. The congestion is a more *severe* form of inefficiency than technical inefficiency (Brockett et al, 2004). This phenomenon arises through under-utilization of innovation capacity (x in Fig 2) by the useless increase of some non-oriented activities. Here, we are rather interested on the under-utilization than reduction because the innovation capacity is a cognitive ability that one has to enhance. In the case of the innovation process, we assume that the congestion phenomenon is explained by the deficiency in the integration of exploratory activities with value-oriented activities. More precisely, the congestion causes in innovation process an under-utilization of:

- Exploration capacity due to lack of relevant questions or directions from the value oriented activities to exploratory ones, to lack of engagement of the exploratory activities with the value-oriented activities or failure to use of the exploratory activities results by the value-oriented ones.
- Design or collective learning capacity due to failure to identify or to explore customer value, difficulty in defining specific domains so that attention can be directed to sources for new solutions, difficulty of selecting the right solutions, transfer of experience preventing the ability to change the rules or lack of routines for analyzing the activity.

Hence within the same enterprise it is possible to find significant activity with regard to knowledge and creativity, but little innovative design and routinized organization.

The degree of congestion is measured by the distance $s^+ = x_M - x_E$ (in input subspace) between the innovation capacity of the enterprise under evaluation (at point M in Fig 2) and that of the postulated efficient enterprise (at point E in Fig 2). The congestion problem can obstruct the implementation of other activities which results in loss φ and s^- (cf. Fig 2) in outputs (Färe and Svensson, 1980), defined respectively as common effect and individual effect. The congestion effects describe the non increasing relationship between the maximum technically feasible output and innovation capacity. The common congestion effect is obtained from the decomposition of aggregate efficiency measure γ so that $\gamma = \eta \times \varphi$ (Byrnes et al, 1984; Kao, 2010). While the individual congestion effect s^- emerges when the efficient projection is not onto the front of Pareto (cf. Fig 2). But here, MOLP-DEA removes this last kind of congestion (cf. section 3).

Finally, the X-efficiency can be evaluated by the distance illustrated by ι (Leibenstein, 1969) between the enterprise under evaluation (at point M in Fig 2) and its efficient projection (at point E in Fig 2). In reality, X-efficiency is the equivalent of the Pareto-Koopmans economical efficiency.

3 Evaluation of X-Efficiency

In this section a MOLP-DEA method is employed under VRS assumption to determine the best practices on the production frontier and the failing practices (cf. section 1). Let us recall that in the context of evaluation of innovation process, we state that the activities are necessarily not reducible (cf. section 2). Therefore, we use output-oriented MOLP-DEA model. As we shall see later unlike classical DEA model, MOLP-DEA provides many efficient solutions in term of innovation intensity and productivity, that are not necessary radial projections. That allows to decision making unit (DMU) to choose the alternative which is best suitable to the innovation strategy developed in its business. Then first of all we evaluate the aggregate efficiency γ (cf. section 2). Clearly, when any component of γ is great than 1 or any slack is not equal to zero we observe an X-inefficiency. In this case, we measure in turn the technical inefficiency, the congestion effect and the congestion rate than degree of congestion, which are components of X-inefficiency. These steps are necessary for the identification of potential internal sources of X-inefficiency for each DMU. Finally we aggregate all these aspects of X-inefficiency with the enhanced DEA Russell graph efficiency measure, to assess overall X-efficiency for each DMU.

3.1 Aggregate efficiency measurement

Suppose we have n DMUs, each using m inputs to produce s outputs. Let $x = (x^1, x^2, \cdots, x^m) \in \mathbb{R}_+^{n\times m}$ the inputs data matrix, $y = (y^1, y^2, \cdots, y^s) \in \mathbb{R}_+^{n\times s}$ the outputs data matrix. Furthermore, we assume that all inputs and all outputs are strictly positives to avoid any solving degeneracy vis-a-vis the constraints. For any DMU_0, we compute its aggregate efficiency γ_0 via the following multiobjective linear program (MOLP):

$$\begin{cases} \max\ (\gamma_0, \lambda_0) = (\gamma_0^1, \gamma_0^2, \cdots, \gamma_0^s, \lambda_0^1, \lambda_0^2, \cdots, \lambda_0^n) \\ \text{ s.t. } \gamma_0, \lambda_0 \in T(x, y, x_0, y_0, \gamma, \lambda) \end{cases} \tag{1}$$

where $T(x, y, x_0, y_0, \gamma, \lambda)$ is the empirical production frontier defined by the output-oriented DEA envelopment model under VRS assumption. Note that within the framework of DEA model, the coefficient matrix of $(\lambda_0^1, \lambda_0^2, \cdots, \lambda_0^n)$ is null, then we have only to maximize the vector $(\gamma_0^1, \gamma_0^2, \cdots, \gamma_0^s)$. The MOLP in program (1) can be solved by various methods to find all efficient solutions γ_0 on $T(x, y, x_0, y_0, \gamma, \lambda)$. In particular, there are many works in the literature that discuss MOLP-DEA for the nearest problematic.

Certain authors like Thanassoulis and Dyson (1992), and Zhu (1996) have developed some models in which the multiple objective is converted into an aggregate unique objective taking into account some *a priori* preference information for the guidance to the target that DMU wishes to attain (cf. also Guan et al, 2006). Here for instance, the assignation of the weights depends upon *a priori* the innovation strategy developed in the business that represents its ideal target. Then these models are said semi-parametric.

Other authors like Lins et al (2004) and Hosseinzadeh Lotfi et al (2009) used the real MOLP to solve the MOLP-DEA in order to provide all efficient solutions. This approach is more appropriate when any directive information is not available. Besides that allows to the DMU to choose *a posteriori* the best alternative compared with its own target.

Note that MOLP-DEA belongs to the class of MOLP problem. Since then all efficient solutions of a MOLP-DEA can be obtained by using either the multicriteria simplex method (Zeleny, 1974; Yu and Zeleny, 1975; Hosseinzadeh Lotfi et al, 2009) or the scalarization method (Geoffrion, 1968; Zeleny, 1974). Obviously, both solving methods provide the same set of efficient solutions. The last method is to assign weights $\omega_0 = (\omega_0^1, \omega_0^2, \cdots, \omega_0^s)$ to each objective that maximizes the scalar $\sum_{r=1}^{s} \omega_0^r.\gamma_0^r$ where $\sum_{r=1}^{s} \omega_0^r = 1$ and $\omega_0^r > 0$ for all r. Likewise, the choice of appropriate alternative depends upon the *a posteriori* optimization criteria of the DMU compared with target to attain.

Furthermore, some variables can be bounded either naturally or by construction. For instance in the business, the innovation capacity is limited because the resource disposability, even in term of activities, is limited. Similarly, innovation intensity is a bounded variable because it reflects the scope of innovation that can be achieved in the business (OECD, 2005). Then we take into account of these constraints in MOLP-DEA model to finding an efficient solution (γ^*, λ^*). Usually, assume that we have two subsets of index $\mathbb{B}_x$ and $\mathbb{B}_y$ for which respectively some inputs and outputs are bounded, then we have to solve the program (1) in two stages to identify the efficient frontier as follows:

Stage 1: For a $DMU(x_0, y_0)$, finding a relative efficient solution $(\gamma_0^{*1}, \gamma_0^{*2}, \cdots, \gamma_0^{*s})$ given a weights system $\omega_0 = (\omega_0^1, \omega_0^2, \cdots, \omega_0^s)$.

$$\left\{\begin{array}{lll} \max \sum_{r=1}^s \omega_0^r.\gamma_0^r & & \\ \text{ s.t. } \sum_{j=1}^n \lambda_j.y_j^r \geq \gamma_0^r.y_0^r & r = 1, \cdots, s \\ L_y^k \leq \sum_{j=1}^n \lambda_j.y_j^k \leq U_y^k & k \in \mathbb{B}_y \\ \sum_{j=1}^n \lambda_j.x_j^i \leq x_0^i & i = 1, \cdots, m \\ L_x^t \leq \sum_{j=1}^n \lambda_j.x_j^t \leq U_x^t & t \in \mathbb{B}_x \\ \sum_{j=1}^n \lambda_j = 1 & \\ \gamma_0^r \geq 1 & r = 1, \cdots, s \\ \lambda_j \geq 0 & j = 1, \cdots, n \end{array}\right. \tag{2}$$

Stage 2: Given the ω_0-efficient solution $(\gamma_0^{*1}, \gamma_0^{*2}, \cdots, \gamma_0^{*s})$ from the program (2), maximizing the output slacks s_0^{r-} and the input slacks s_0^{i+} as follows.

$$\left\{\begin{array}{ll} \max \sum_{r=1}^s s_0^{r-} + \sum_{i=1}^m s_0^{i+} & \\ \text{ s.t. } \sum_{j=1}^n \tilde{\lambda}_j.y_j^r - s_0^{r-} = \gamma_0^{*r}.y_0^r & r = 1, \cdots, s \\ L_y^k \leq \sum_{j=1}^n \tilde{\lambda}_j.y_j^k \leq U_y^k & k \in \mathbb{B}_y \\ \sum_{j=1}^n \tilde{\lambda}_j.x_j^i + s_0^{i+} = x_0^i & i = 1, \cdots, m \\ L_x^t \leq \sum_{j=1}^n \tilde{\lambda}_j.x_j^t \leq U_x^t & t \in \mathbb{B}_x \\ \sum_{j=1}^n \tilde{\lambda}_j = 1 & \\ \tilde{\lambda}_j \geq 0 & j = 1, \cdots, n \end{array}\right. \tag{3}$$

It is clear that each ω_0-efficient solutions provides an input slacks. Note that the efficient frontier provided by MOLP-DEA is the same than variant classical model as radial, additive or slack based models. But unlike the latter, MOLP-DEA suggests various efficient alternatives (cf. Fig 3) to the DMU under evaluation for some $\omega_0 = (\omega_0^1, \omega_0^2, \cdots, \omega_0^s)$ (Geoffrion, 1968; Zeleny, 1974). Thereby any DMU exhibits non positive output slacks s_0^{r-}. Then the $DMU(x_0^i - s_0^{i+}, \gamma_0^{*r}.y_0^r)$ determine the empirical efficient frontier.

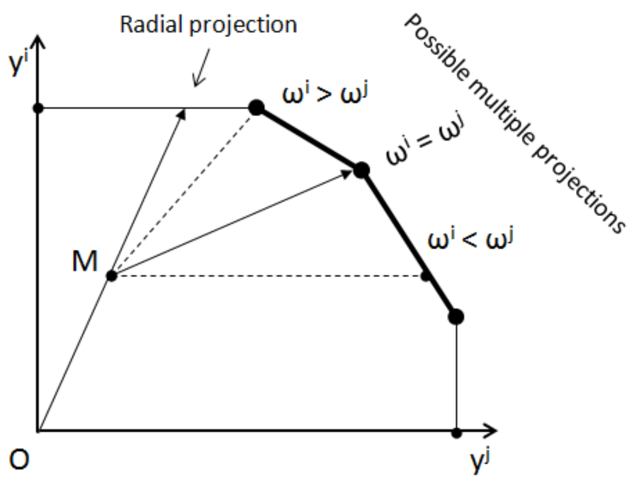

Fig. 3 Comparison between radial DEA projection vs. MOLP-DEA projection. Here if $\omega^i > \omega^j$ that means objective i is more important than objective j. Then an inefficient DMU is more penalized on the objective i than j.

Here, we emphasize that $(\gamma_0^{*1}, \gamma_0^{*2}, \cdots, \gamma_0^{*s})$ is the vector of aggregate (output) efficiency for the DMU under evaluation observed on each output. That is not the X-efficiency defined in section 2 because it does not take into account the eventual congestion problem exhibited in input slacks as useless increase of non-oriented activities due to lack of interplay. Then we say that a DMU is X-efficient when:

(a) $\gamma_0^{*r} = 1$ for all r
(b) $s_0^{i+} = 0$ for all i

When $\gamma_j^{*r} = 1$ for all r, we say that the DMU is only $\gamma-$*efficient*. Hence a DMU can appear $\gamma-$efficient without being X-efficient. Although γ is incomplete for the evaluation of X-efficiency, by contrast it is necessary in the next section for the partitioning of it in order to know whether the X-inefficiency is due to technical inefficiency or congestion effect. As well in the last case, we evaluate the congestion rate.

3.2 Technical efficiency and congestion measurement

In section 2, we have clarified that X-inefficiency can appear under technical form, congestion forms or both technical and congestion forms. According to (Färe and Svensson, 1980; Brockett et al, 2004), the congestion appears when one input is increased, any output falls in the wide sense. Let us recall that output loss due to input increase is the input congestion effect. But γ does not distinguish the technical inefficiency from the congestion effect. Note that the congestion is a severe form of inefficiency in the sense where finding a technique allowing to achieve input reduction accompanied output improvements (Brockett et al, 2004). In practice, that means moving from $DMU(x_0^i, y_0^r)$ to $DMU(x_0^i - s_0^{i+}, \gamma_0^{*r}.y_0^r)$. Then we must to find the coordinates point $DMU(x_0'^i = x_0^i, y_0'^r = \eta_0^{*r}.y_0^r)$ on the production frontier whom the $DMU(x_0, y_0)$ can improve its outputs without necessarily reduce any inputs. We obtain this point with the model developed by Tone and Sahoo (2004) described in the following program (4):

$$\begin{cases} \max \sum_{r=1}^{s} \omega_0^r.\eta_0^r & \\ \text{s.t.} \sum_{j=1}^{n} \lambda'_j.y_j^r \geq \eta_0^r.y_0^r & r = 1, \cdots, s \\ L_y^k \leq \sum_{j=1}^{n} \lambda'_j.y_j^k \leq U_y^k & k \in \mathbb{B}_y \\ \sum_{j=1}^{n} \lambda'_j.x_j^i = x_0^i & i = 1, \cdots, m \\ L_x^t \leq \sum_{j=1}^{n} \lambda'_j.x_j^t \leq U_x^t & t \in \mathbb{B}_x \\ \sum_{j=1}^{n} \lambda'_j = 1 & \\ \eta_0^r \geq 1 & r = 1, \cdots, s \\ \lambda'_j \geq 0 & j = 1, \cdots, n \end{cases} \tag{4}$$

When the $DMU(x_0^i, \eta_0^{*r}.y_0^r)$ is in the area under the congestion effect, clearly we have $\eta_0^{*r} \leq \gamma_0^{*r}$. From this inequality, we decompose the aggregate efficiency $(\gamma_0^{*1}, \gamma_0^{*2}, \cdots, \gamma_0^{*s})$ by separating the technical inefficiency[6] $(\eta_0^{*1}, \eta_0^{*2}, \cdots, \eta_0^{*s})$ from congestion effect $(\varphi_0^1, \varphi_0^2, \cdots, \varphi_0^s)$ by the following relation $\gamma_0^{*r} = \eta_0^{*r} \times \varphi_0^r$ (Byrnes et al, 1984; Kao, 2010). This distinction allows us to know whether an inefficient DMU suffers more the congestion effect than the technical inefficiency. The program (4) is the same that the program (2) except the input constraints.

Moreover when congestion occurs, we can also measure the congestion rate in each group of activities. Zhu (2000) proposed a measure of this phenomenon based on the slacks in inputs, which is defined for the $i-th$ input by:

$$\tau_J^i = \frac{\sum_{j \in J} s_j^{i+}}{\sum_{j \in J} x_j^i} \tag{5}$$

where J is a category of DMUs (for instance size or technological sector), s_j^{i+} are the input slacks provided in program (3) for any DMU_j. This quantity enables us to appreciate the rate of under-utilization of innovation capacity in this group.

Now, we have all elements of the X-efficiency assessment as the technical efficiency measure η, the congestion effect measure φ and the congestion rate measure τ. Note that these every measures are great than one, then we take their inverses so that they range from zero to one. These information enable only us to locate the source of X-inefficiency but do not indicate the magnitude of this X-inefficiency. In the next section, we shall develop this topic.

3.3 X-Efficiency measurement

Let us recall that we only know that DMU is X-efficient when $\gamma_0^{*r} = 1$ for all r and $s_0^{i+} = 0$ for all i. Otherwise, we cannot know how far a DMU under evaluation is X-inefficient. According to Leibenstein and Maital (1992), aggregate efficiency γ_0 measures only a part of X-inefficiency because each component

[6] Note that other authors like (Byrnes et al, 1984) and (Kao, 2010) use the term pure technical inefficiency.

γ_0^r measures only the possible proportional expansion in each output. Then for instance the use of the weighted Russell measure $\overline{\gamma}_0 = \sum_{r=1}^{s} \omega_0^r.\gamma_0^r$ can cause a miss measurement because two DMUs can have the same X-efficiency score $\overline{\gamma}$ whereas they are compelled to adjust their activities in different manner. Indeed, γ_0 projects $DMU(x_0, y_0)$ under evaluation onto $DMU(x_0^i, \gamma_0^{*r}.y_0^r)$ but not onto true efficient projection $DMU(x_0^i - s_0^{i+}, \gamma_0^{*r}.y_0^r)$.

To take into account of all aspects of X-inefficiency, Leibenstein and Maital (1992) suggested the use of the weighted euclidean ι in the case of the input-oriented model. However, this index is only appropriate when any inefficiency does not occur on all outputs. Especially since a distance ranges from zero to infinity, this approach is not easily adaptable to a efficiency measure.

Pastor et al (1999) performed the Russell graph efficiency measure as the enhanced DEA Russell graph efficiency measure, defined as follows:

$$R_e(x_0, y_0) = \left(\frac{1}{m}\sum_{i=1}^{m}\theta_0^i\right) \Bigg/ \left(\frac{1}{s}\sum_{r=1}^{s}\gamma_0^r\right) \tag{6}$$

where $\theta_0^i = \frac{x_0^i - s_0^{i+}}{x_0^i}$ and s_0^{i+} is provided by the program (3). In their work, the authors provided the computational aspects to calculate this index. But here, we directly obtain it from the MOLP-DEA in programs (2) and (3). This approach seems us being the best alternative to assess the X-inefficiency vis-a-vis previous remarks and concepts defined in section 3. Indeed, it decreases when we observe useless increase of any input associated with decrease of any output (cf. Pastor et al, 1999).

Note that, by contrast to technical efficiency (3.2), the X-efficiency is not always attainable. Because, a DMU can technically improve its innovation process without as far as eliminating all inefficiency like the congestion for reasons exposed in section 2.2. Although the X-inefficiency really reflects the magnitude of all inefficiency.

4 Empirical analysis

4.1 Data

Most of the data come from a representative sample of 80 innovative enterprises from the 803 SMEs in the manufacturing sector of the region of Normandy in France. These enterprises are divided following three stratum variables: (a) the size divided into three categories as less than 20 employees (-20), from 20 to 50 employees ($20 - 50$), more than 50 employees ($+50$); (b) the technological sector level (TSL) divided into three categories as lower technology (LT), Medium lower technology (MLT), medium high technology (MHT). Data are gathered through interviews with the entrepreneurs using a set of questions (Gaussens and Houzet, 2009) relating to the strategies and processes of the enterprise. The questions deal with to the innovation strategy and innovation process that the entrepreneur followed from 2006 to 2008.

Let us recall that innovation intensity and innovation capacity are latent variables because they are not directly observable (Hansen, 2001). Nevertheless, they can be measured by manifest variables directly observable in the enterprise like the achieved innovation or the activities. From this survey, we selected 231 categorical basic indicators as observable indicators of activity. They are grouped into five categories, for each an aggregate indicator was constructed (cf. Table 1). Each of the first four aggregate indicators is obtained from the observable indicators of appropriate activities (cf. Table 1) making up the innovation process indicators.

These are indicators of innovation capacity for each type of activities in the innovation process. They are inputs to the process and measure the innovation capacity of the enterprise (cf. Table 1). Numerically, the capacity in each type is determined by the dimension of the set of activities observed in one enterprise, normalized the maximum dimension of all observable activities as in formula (7). For instance, if an enterprise does not engage any design activity (or all possible activities), its design capacity is null (or maximum equal to 1).

$$Design\ capacity = \frac{Observed\ activities\ of\ design}{Possible\ activities\ of\ design} \tag{7}$$

The aggregate innovation intensity indicator (cf. Table 1) is obtained from kinds of innovation achieved by the enterprise (cf. formula 8). It is one of outputs of the innovation process. Numerically, the innovation intensity is likewise computed in the same way the innovation capacity. Hence, an enterprise which does not engage any kind of innovation, said not innovative, has a null intensity.

$$Innovation\ intensity\ (II) = \frac{Achieved\ innovations}{Possible\ innovations} \tag{8}$$

In addition, we use the total factor productivity (cf. Table 1) TFP as second output indicator of the innovation process. It is measured using an index calculated from the financial data of individual enterprises[7] (Grupp and Maital, 2001) and normalized.

Hence all aggregate indicators of innovation capacity and of innovation output range from 0 to 1.

Table 1 Inputs and outputs indicators.

Aggregate indicators		Basic indicators	It./Ind.[a]
Value oriented activities			
	Design activities	Design methods	12
		Design scope	11
		Market needs identification	7
		Products and methods description	20
		Change and areas of exploration	11
		Selection of solutions	28
		Risk management	5
		Project management	4
		Human resources management	1
	Organizational learning activities	Learning scope	9
		Feedbacks	3
		Experimentations with new situations	5
		Strategic deployment	2
		Routines	6
		Working group on problem solving methods	1
Exploratory activities			
	Knowledge activities	Knowledge management	7
		Internal production of knowledge	11
		External sources of knowledge	36
		Risk management	1
		Knowledge community management	13
		Funding research	1
		Human resources management	4
	Creativity activities	Creativity tools	2
		Search of new solutions	9
		Team management	5
Outputs of innovation			
	Innovation intensity	Product innovation	2
		Process innovation	3
		Marketing innovation	4
		Organization innovation	4
		Diversity of innovations	3
	Total factor productivity		1

[a]Number of items per basic indicators.

[7] $TFP = VA/(L^{\alpha}.K^{1-\alpha})$ where VA: overall value added, L: number of employees, K: capital, α: fraction of value added attributable to labor.

Table 2 Descriptive statistics on the indicators.

Indicators	Min	Mean	Max	St.Dev.
Outputs of innovation process				
Total factor productivity	7.81	21.44	40.6	7.83
Innovation intensity	0.03	0.28	0.80	0.18
Inputs of innovation process				
Design capacity	0.08	0.30	0.67	0.13
Capacity to explore and to exploit the knowledge	0.04	0.23	0.48	0.10
Creativity capacity	0.01	0.33	0.65	0.15
Organizational learning capacity	0.16	0.52	0.88	0.19

4.2 Empirical results

In this analysis, all estimations are provided by using the scalarization method and based on the assumption that innovation intensity and TFP have the same importance. We used nonparametric tests as the binomial test, Wilcoxon signed rank test and Kruskal-Wallis test in order to establish the results. Results are summarized in the following table.

Table 3 Average score results.

Categories	F./C.[b]	$\overline{R_e}$	$\overline{\gamma}_{TFP}$	$\overline{\gamma}_{II}$	$\overline{\eta}_{TFP}$	$\overline{\eta}_{II}$	$\overline{\varphi}_{TFP}$	$\overline{\varphi}_{II}$
Size								
-20	35	0.59	0.80	0.69	0.93	0.87	0.86	0.79
$20-50$	32	0.59	0.88	0.64	0.94	0.87	0.94	0.74
$+50$	13	0.55	0.78	0.64	0.89	0.79	0.89	0.82
TSL								
LT	35	0.55	0.75	0.68	0.88	0.84	0.85	0.80
MLT	26	0.55	0.87	0.60	0.96	0.87	0.91	0.71
MHT	19	0.70	0.92	0.74	0.96	0.89	0.96	0.81
Average scores		0.59	0.83	0.67	0.92	0.86	0.9	0.78

[b]Number of firms per category.

Firstly, our estimates show the relative importance of inefficiency in the innovation processes of SMEs:

(a) 71.25% of innovation processes are X-inefficient ($p.value \ll 0.0001$). In addition, neither the technological sector nor the firm size area are determinants of X-efficiency ($p.value$ are resp. equal to $0.2285, 0.8887$). That means for any size or any technological sector level, enterprises use the same innovation technology.
(b) Inefficiency in the innovation process appears most frequently as a congestion problem ($\overline{\eta}_{II} > \overline{\varphi}_{II}$ and $p.value = 0.0510$). In addition we observe non-zero rate of congestion on almost inefficient processes in at least one activity group. In particular, we find that 89.39% of inefficient processes have non-zero rates of congestion simultaneously in exploratory activities and in value-oriented ones (respectively 20.04% and 20.19%).
(c) Creativity capacity and in organizational learning capacity are particularly under-used and under-exploited: the congestion rate is significantly higher in these activities (respectively 25.49% and 27.58% against 6.55% in design and 12.6% in knowledge).

Secondly, the multiobjective analysis enables us to characterize the inefficiency in respect to innovation intensity and productivity:

(a) The average level of innovation output is lower in inefficient SMEs. Efficient innovation processes significantly generate instead higher productivity ($p.value = 0.0267$). However in innovation intensity, the level difference is not significant ($p.value = 0.4522$).

(b) In average, inefficiency is significantly characterized more by a lack of innovation intensity than by a lack of productivity (cf. Table 3):
- $\overline{\gamma}_{TFP} > \overline{\gamma}_{II}$, $(p.value = 0.0005)$
- $\overline{\eta}_{TFP} > \overline{\eta}_{II}$, $(p.value = 0.0808)$
- $\overline{\varphi}_{TFP} > \overline{\varphi}_{II}$, $(p.value = 0.0005)$

5 Conclusion

The MOLP-DEA method allowed us to clarify two points. Firstly, it allows us to highlighting the difficulties that the majority of entrepreneurs have in organizing efficiently their innovation processes in the sense where there is more failure in innovation intensity than in productivity. Secondly, it enables us to identifying the internal sources of inefficiencies.

This paper makes two contributions. Firstly we developed the concept of X-efficiency from the works of Leibenstein (1966, 1969, 1977) and adapted it to the case of the innovation process. For that, we have defined each component of X-inefficiency and specified their appropriate measure. Secondly, we suggested the use the enhanced DEA Russell graph efficiency measure to evaluate the X-efficiency of innovation process defined in section 2 from MOLP-DEA. This approach enabled us to overcome the difficulties related to the index based on the proximity introduced by Leibenstein and Maital (1992).

Thus our analysis shows that the inefficiency of the innovation process assumes a particularly severe form in congestion as fundamental under-utilization of innovation capacity. It results from the non-implementation by the entrepreneur of efficient rules or standards of interplay in certain areas of the collective design of the business. A majority of inefficient enterprises develop activities of knowledge and creativity. But paradoxically, they are characterized by little innovative design and routine organization. This under-utilization needs to be reduced: (a) by the establishment of novel rules and standards of interplays to managing such situation in order to orient all activities to the best production technically realizable; (b) by identification of superfluous activities in order to rectify the innovation capacity so that its allows to improve the productivity and the innovation intensity. But in practice, both options are more difficult to achieve because any novel adjustment needs and can cause other involvements.

The MOLP-DEA led us to a better understanding of the relationship between the different outputs of an innovation process (innovation intensity and TFP) and the efficiency of the latter. Going beyond a simple approach that explains productivity directly by the innovation intensity, the MOLP-DEA suggests that innovation process efficiency may account for greater productivity, and that greater innovation intensity could explain higher efficiency through a learning effect.

Finally, higher productivity could explain higher innovation intensity through a self-selection effect. Further work will need to develop these lines of research to achieve a more realistic approach to process innovation in SMEs.

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