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X-Efficiency of Innovation Processes: Concept and Evaluation based on Data Envelopment Analysis

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Abstract

This paper investigates X-(in)efficiency of innovation processes in Small and Medium-sized Enterprises (SMEs). We have adopted the following approach: (a) we provide both a concept of X-(in)efficiency and a model of innovation processes for each SME; (b) from this model we evaluate both the dimensions of the innovation processes and the X-(in)efficiency of these processes using a variant of the Data Envelopment Analysis (DEA) model; (c) finally, we characterize X-inefficiency by using techniques of exploratory analysis derived from an empirical analysis. Our approach has been applied to regional SMEs in Normandy (France) with a representative random sample of 80 innovative businesses. The results show the existence of X-inefficiency in the innovation processes of SMEs in 71% of cases. This X-inefficiency arises primarily from the difficulties that entrepreneurs face in implementing the interacting rules and standards of exploitation and exploration activities.

Keywords: Data Envelopment Analysis, Multiple Projections, X-Efficiency, Innovation Process.

1. Introduction

In small and medium-sized enterprises (SMEs), innovation is an undisputed source of competitiveness and growth (Guan et al., 2006). However, the development of innovation strategies depends upon a better understanding of the innovation process. We therefore need to clarify our conception of innovation and the innovation process. Using the Oslo Manual (OECD, 2005), we consider innovation to be 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. At the same time, this manual describes innovation as a permanent, dynamic and evolutive process, but does not adequately define properly the innovation process itself. However, Chesbrough and Rosenbloom (2002) have defined the innovation process as one which transforms strategic, technological and non-technological knowledge specific to the entrepreneur into business process (new value) under conditions of uncertainty. Here we adopt this last definition of the innovation process.

In addition, much theoretical and empirical work on innovation and business has focused on two fundamental points regarding innovation: the role of SMEs, and the influence of organization (Cohen, 1995; Rothwell and Dodgson, 2004). However, as far as we know, there is no study that explores the efficiency of innovation processes in these organizations, despite this

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question being of importance to the decision making units (DMUs) developing action plans for better innovation strategies. Only one study, covering innovative firms in China and carried out by Guan et al. (2006), has investigated the efficiency of innovation harmonizing processes, which is an input-output system of competitiveness. This study does not deal with the efficiency of the innovation process as defined previously. On the other hand, a recent survey undertaken in the IDEIS project¹ has shown how unsatisfactory the development of business innovation in the majority of SMEs in the Normandy region is. The main issue is whether this phenomenon is due to the inefficiency of their innovation processes. The same survey has also revealed that most entrepreneurs see the innovation process as more or less a black box. In fact, this perception derives from those aspects of innovation that are not directly measurable or observable, or are even intangible (Hansen, 2001; Guan et al., 2006). In reality, innovation is a latent variable. This situation often causes difficulties for entrepreneurs modeling their innovation processes, in identifying and measuring the dimensions of innovation, such as inputs and outputs. It may even be the cause of the inefficiency of their innovation processes.

Our study is motivated by these three main points: first, we propose a modeling of the innovation process using some procedures established in the literature. Here we also identify the dimensions of the innovation. Secondly, using this model, we propose an evaluation model of the efficiency of innovation process. We show both the existence of X-inefficiency in the innovation processes, and that inadequate development of innovation in SMEs is related to it. Finally we provide some characterizations of the inefficiency.

In the literature on the measurement of the innovation, certain authors (Chiesa et al., 1996; Dodgson and Hinze, 2000; Hansen, 2001) propose some audit tools based on observable indicators to enable decision makers to collect data on innovation. Relating to the same issue, 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 (CIS²). 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, 2009) from which we have selected a collection of evaluation criteria.

Moreover, the innovation process is a multidimensional and complex event with multi-inputs (activities) and multi-outputs (Hansen, 2001; Guan et al., 2006). It involves a range of activities, involving financial, material and immaterial resources. Here we focus more on the analysis of the activities coordinated by the entrepreneur than on the use of economic resources. Indeed, in line with Amit and Schoemaker (1993), the capacity for innovation enables a business to make us of its resources in the activities that make up the innovation process: design, organizational learning, and activities related to knowledge and creativity.

Otherwise we consider two outputs from the innovation process: innovation intensity and total factor productivity (TFP). Innovation intensity takes into account the different types of innovation³ that can be achieved in a business. It measures the scope of innovation. The

¹The 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.

²cf. <http://epp.eurostat.ec.europa.eu/portal/page/portal/microdata/cis>.

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

TFP measures how far this particular business makes use of its innovative activities. This suggests that a priori these two indicators each have the same importance in the objective function for the decision maker. In the other words, the innovations made in the business are: (a) through the innovation achievements of the business; (b) the monetary translation of significant improvements that have been introduced in a particular domain of the business⁴.

Furthermore 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 business than a well-defined process based on dedicated resources, such as formal R&D, and deployed as part of a strategy. Therefore we deal with the X-efficiency or X-inefficiency of an organization due to Leibenstein (1979).

X-inefficiency regroups non-allocative inefficiencies. X-inefficiency theory is concerned with the under-utilization of resources - (...) *what was involved by and large were the activities inside business (...)* - (Leibenstein, 1979). For example labor, capital and information may not be fully used, or may be ineffectively used, or rules and procedures used in the business may turn out to be inadequate in the current context. Then, given the main characteristics of an innovation process (uncertainty, interactivity, cognition), it is easy to understand why this process is characterized by X-inefficiencies - (...) *the conclusion that without introducing an X-inefficiency factor into his equations, the innovation process and the rate of innovation could not be explained (...)* - (Leibenstein, 1979). In the context of the innovation process, X-inefficiency causes a non-optimal use of innovation capacity. The enterprise can then suffer a loss of productivity or insufficiency of innovation.

Here we investigate the sources of under-utilization of innovation capacity. There are two principal contributions made in this paper: (1) the specification of some aspects of X-inefficiency in innovation processes such, as the problems of technical inefficiency and congestion; (2) measuring the respective magnitude of each phenomenon, and also global X-inefficiency.

X-inefficiency can be evaluated using parametric or nonparametric methods. The parametric approaches require satisfactory specification of the functional form and the distribution of random production. Moreover, in multi-input and multi-output systems all output dimensions have to be aggregated. In such conditions it is difficult to establish the parameters of the technology. Guan et al. (2006), Leibenstein and Maital (1992) have, respectively, proposed the use of data envelopment analysis (DEA) to analyze the efficiency of innovation harmonizing processes, and the X-efficiency of an organization. In this paper we employ the DEA method to evaluate the components of X-efficiency of innovation processes. Since there is also a lack of information on the nature of technology innovation, we use the DEA model under variable returns to scale (VRS) to estimate the empirical technology and, the enhanced Russell graph efficiency measure for an assessment of the magnitude of X-inefficiency.

The evolution of outputs depends on market structures which determine the innovation strategy of the business. For example, a business 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 to maintain its TFP. In this situation, we can observe a high level of innovation intensity. That means innovation intensity and TFP are uncontrollable variables. Comparing the DMU with a radial projection is not then really appropriate, especially if this projection is a convex

⁴An business is regarded as innovative if it introduced at least one type of innovation (product, process, marketing or organization) from 2006 to 2008 (Gaussens, 2009).

combination of efficient units, but not a real DMU. Therefore we use the multiple projections DEA model to identify all possible efficient peers of the DMU under evaluation. Then we choose an appropriate projection among them with respect to an appropriate distance (e.g. cf. [Yang et al., 2009](#), about the shortest distance model in the MOLP-DEA). Besides, in some cases authors such as [Lins et al. \(2004\)](#) and [Hosseinzadeh Lotfi et al. \(2009\)](#) have suggested the use of multiobjective linear programming in a DEA (MOLP-DEA) model to identifying all efficient DMUs.

This paper is organized as follows. In section (2) we provide a model of the innovation process as an interactive process between exploitation and exploration. We also describe both the concept and the aspect of the X-(in)efficiency in the innovation processes. In section (3), we propose both a measurement model of innovation and an evaluation model based on the data envelopment approach of the X-(in)efficiency. In section (4), we conduct an empirical analysis of innovation processes in SMEs of the Normandy region of France with data from the IDEIS project survey. We also identify the sources of X-inefficiency by partitioning X-inefficiency. Finally, we propose in section (5) some description and characterization of X-inefficiency by combining two techniques of exploratory analysis, recursive partitioning and multiple correspondence analysis.

2. X-Efficiency in the innovation process

We model the innovation process from works on the exploration/exploitation trade-off in organizational learning ([March, 1991](#); [Nooteboom, 2001](#); [He and Wong, 2004](#); [Holmqvist, 2004](#); [Harryson, 2008](#)), and also from design theory ([Simon, 1969](#); [Schön, 1984](#); [Kline and Rosenberg, 1986](#); [Hatchuel and Weil, 2009](#); [Le Masson and Weil, 2010](#)). The innovation process is considered here as a process of innovative design characterized by interactions⁵ between value-oriented or problem solving/solution focused activities (or exploitation⁶), and explorer oriented activities⁷ (for further details see [Appendix A](#)). We consider design activities oriented to the definition of value, and organizational learning oriented to the collective capacity to realize value. Knowledge activities and creative activities are exploratory to the extent that they allow the value-oriented activities to explore potential value and orient themselves towards innovation. We assume that, from the efficiency of innovation in SMEs, the key question is how to better integrate exploration and exploitation⁸. Indeed, radical incrementalism or intensive innovation is well adapted to this type of enterprises in the sense that this innovation model is based on the co-evolution of values and knowledge ([Le Masson et al., 2010](#); [Forsman, 2011](#)).

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 or exploitation. Also, this X-efficiency depends more on interactions between the activities than on a simple balance between them, with the necessary and sufficient innovation capacities level equal. The X-efficiency means here the existence and the optimal use of relevant rules, standards or procedures of in the interactions between individuals and different business

⁵Interact in a process in an enterprise means to act by addressing customers or users.

⁶According to [March \(1991\)](#), the efficient use of existing knowledge.

⁷The development of new knowledge ([March, 1991](#)).

⁸Maintaining a balance between exploitation and exploration turns out to be very difficult ([Adler et al., 2009](#)). Concerning complementarity between exploitation and exploration, see the many research studies relating to the *ambidextrous organization*, as initiated by [Tushman and O'Reilly \(1996\)](#).

activities in the organization⁹ within which the process of collective design is developed¹⁰ This process generates a co-construction of collective activity based on a continued expansion of questions from value oriented activities and possible solutions deriving from exploratory activities according to [Simon \(1986\)](#)¹¹. More precisely, we define the innovation process as a network of activities, centered on the entrepreneur function. The entrepreneur knows the products, the technologies and the markets in which his business is evolving. He is best able to model, organize and stimulate tailored interactions between exploration and value creation ([Harryson, 2008](#); [Gobbo Jr. and Olsson, 2010](#)). The answer to the problem of the adjustment between exploration and exploitation lies in either minimizing innovation capacities, risking little or no innovation output (natural tendency displayed by existing organization ([Adler et al., 2009](#))), or as in the entrepreneurial response, driving the innovation dynamics of enterprise ([Tushman and O'Reilly, 1997](#)). Within this last framework, we see the entrepreneurial function as a management system based on designing and organization learning from schemes used to link exploration and exploitation. Designing schemes are intended to the definition of the value for the enterprise. These are fundamentally based on interactions between the designing actors and the customers or external users. The quality of these interactions is a critical factor in determining the relevance of questions defining directions to be explored (in which areas is research needed, and what solutions must be found ?); and also the relevance of screening or selection for proposed ideas and solutions. For example, the poor quality of **man/machine** interfaces is due to the lack of interactions between designers and ergonomists, which is itself explicable by the separation between designing and using.

Learning mechanisms are applied jointly in a complementary manner¹² to establish the value. Their effectiveness is based on relevant patterns of strengthened interactions between drivers and implementers in the innovation process changing rules and procedures through an exploratory approach. Strategic deployment, feedback concerning experience, knowledge capitalization **test/error experimentation**, these are all practices related to organizational

⁹The possibility of interactions between individuals requires that they relate to each other, which is based on communication, coordination and cooperation rules and media, such as the possibility of meeting and having unexpected conversations, on contracts and agreements, a shared language and a common knowledge.

¹⁰Given that designing refers to prescribing (knowing what must be done and how, checking the implementation), the concept of collective designing relates to **low prescription** and **reciprocal prescription** ([Hatchuel et al., 2002](#)) in a context of interactive rationality ([Ponssard and Tanguy, 1993](#)).

¹¹Simon's key contribution has been to highlight the interaction between exploration and problem-solving. When problems are ill-defined, as is the case in innovative design, both problems and solutions arise. It is therefore a type of problem-solving that is resolved by drawing up so-called cognitive strategy **focused-solution** that leads to specify objectives and original constraints. This approach has been formalized in the framework of the C-K theory developed by [Hatchuel and Weil \(2009\)](#).

¹²First, the quality of collective designing depends on the quality of interactions between actors in the process seeking to reach agreement on what needs to be done. The quality of interactions itself depends on the smooth conduct of the interpretative work by reciprocal discussion based on rules and standards of interactions ([Schön, 1984](#)). Those need to be updated as required by the renewal of knowledge essential for innovative design ([Le Masson et al., 2010](#)). Finally, interactions in the designing process should be oriented towards the realization of value, and conversely the transaction should be designed to make interactions workable. For example, the separation between designing buildings and their construction tends to lend precedence to financial and commercial criteria at the expense of safety ([Lorino, 2007](#)).

learning (March, 1991)¹³. Thus cooperation between Renault and General Motors (GM)¹⁴ over the design of the Traffic van initially encountered difficulties because the representatives of each firm adhered too closely to the standards of their own company. Once this was discovered a corporate decision was made to develop principles specific to the process of co-operation, deviating from those of Renault and GM.

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 Figure (1).

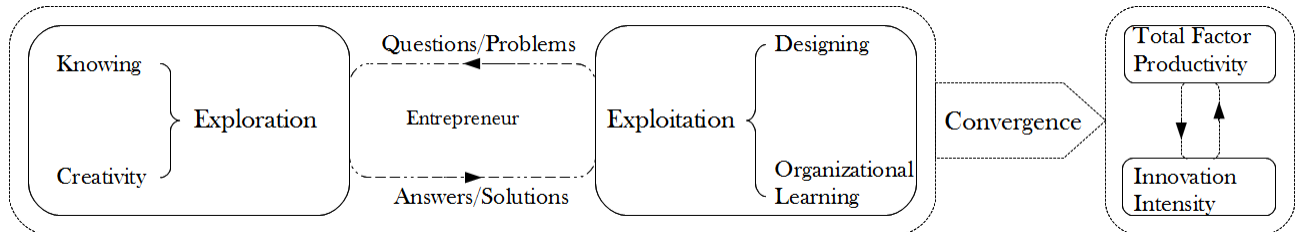


Figure 1: Innovation process as collective design process (cf. Appendix A for details).

From the point of view of efficiency, we generally consider that it is difficult to balance exploration and exploitation, in that some of the knowledge, learning and proposed solutions will ultimately not be recovered or used (Le Masson et al., 2010).

The excess of exploratory activity can be explained by the filtering and selection in the process of convergence towards the achievement of value. We are assuming here that the adjustment problems between exploration and exploitation are based not only on defects in knowledge capitalization and ultimately in their re-use, but more broadly on failures of interaction which may result in under-utilization of both exploration and exploitation. Thus separating designing from using will produce both excess in design and under-utilization of user’s knowledge, in relation to the value that could have been produced if appropriate interfaces had been introduced. Additionally, an overly prescriptive process, or an excessively hierarchical structure, prevents actors closely involved in the process to assume responsibility for adapting and providing reliable feedback. This results in the under-utilization of implementer’s knowledge and experience, and as a corollary, an excess of rules, procedures, incentives mechanisms and control.

We are assuming here that the failures of interaction which produce under-utilization of both exploration and exploitation explain the way that many businesses operate with a considerable degree of slack and are X-inefficient, according to Leibenstein (1968, 1969, 1979). In turn, this implies the existence of entrepreneurial opportunities (Leibenstein, 1968). The failures of interaction between actors and/or professionals in the innovation process (including actors external to the enterprise: customers, users, suppliers and others usual or unusual sources of knowledge¹⁵) result in both a lack of use of knowledge and experience from these actors, and their lack of motivation¹⁶. Indeed, interactions have not occurred naturally, they must be

¹³Provided these practices are reliable, since that depends on relevant rules and procedures of interactions between drivers and implementers in the innovation process. For example, room for error and low hierarchical pressure promote upward relevant feedback (Pfeffer and Sutton, 2006). Strategic execution depends upon a well-conceived strategy and its effective implementation through explanation and discussion.

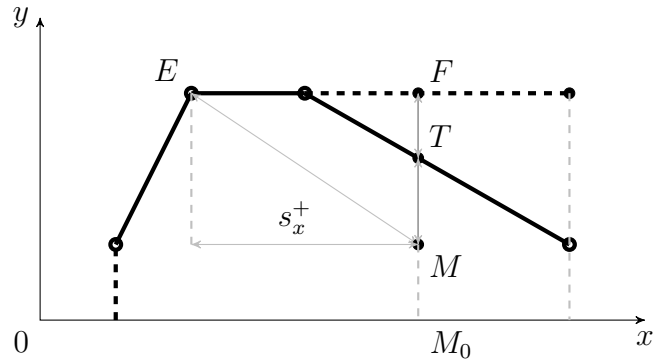
¹⁴Example from Morel (2012, p.159).

¹⁵For example, the entrepreneur Gustave Eiffel was an exceptional organizer of collective innovative designing activities, involving unusual actors such as artists, ministers or provincial governors (Le Masson et al., 2010).

¹⁶The under-exploitation of knowledge and the lack of employee motivation are at the heart of the X-

Figure 2:

Graphical illustration of the X-Inefficiency. The empirical frontier is delimited by the thick full line.



well thought have to be adequately conceived and properly and properly organized by the entrepreneur, whose role. Obviously that its role of contributing to lies in creating a corporate culture and a set of practices which allow the construction of conducive to a collective process of innovation (Pfeffer and Sutton, 2006). Entrepreneurial failure is the prime explanation of X-inefficiency of the innovation process in the enterprise: "...the essential aspects of the requisite entrepreneurial activities are to fill lacunae in the production function, in the organizational structure, in the incentive-reward system, or in any other part of the structure of the firm or the economy necessary to promote changes." (Leibenstein, 1969, p.612).

Thus inappropriate interaction causes technical inefficiency. The technical inefficiency of the innovation process is centered on output, since the aim is to gain the best return with optimal innovation capacity from the process activities. Technical inefficiency here means: the relatively defective implementation of relevant patterns of interaction in the collective design process which prevent the achievement of the optimal pace of individual activities (for example in the case of the inefficient cooperation between Renault and GM, see above). This can hinder achievement of the optimum level of productivity or innovation. In that case, the entrepreneur needs to improve interaction techniques, for example by improving the information system to speed up the circulation of information, and improve the sharing of knowledge, maintaining the innovation capacity of the business and eliminating this form of X-inefficiency (cf. Figure (2)).

Technical inefficiency is measured by the illustrative distance $\eta = M_0T/M_0M$ between the actual output of the DMU under evaluation (at the point M in Figure (2)) and the observable DMU achieving the maximum technically feasible output with the same capacity for innovation (at the point T in Figure (2)).

Congestion is a more severe form of X-inefficiency than technical X-inefficiency (Cooper et al., 2001; Brouckett et al., 2004). It is a special phenomenon of the production process whereby larger amounts of some inputs cause lower levels of some outputs (Färe and Svensson,

inefficiency in the innovation process: "I argued that neither individuals nor groups (firms) work as hard or as effectively or search for new information and techniques as diligently as they could..." (Leibenstein, 1968, p.75). Knowledge does not move, individuals should build their own knowledge through the interactions which the organization enables them to implement. It is up to the entrepreneur to promote curiosity and willingness to learn in his teams by giving meaning in what they do: "It seems reasonable to believe that people are likely to be happier when their work is more meaningful, and this is likely to be positively associated with X-inefficiency." (Leibenstein, 1979, p.17). For example well-known innovative companies such as IDEO or SAS have adopted the strategy of listening to their employees and their customers; or in the case of Xerox, whose recovery is not due to a brilliant strategy, but due to the commitment of its employees to pursue common goals (Pfeffer and Sutton, 2006).

1980). It is the lack of combinations and technical drivers for the available inputs that results in the excess, or under-utilization, of inputs. In practice this is why, in contrast to technical efficiency, X-efficiency is not easily attainable (Lins et al., 2004). In our case, it comes from the non-implementation of relevant patterns of interactions in certain areas of the collective design of the business. The lack of interaction leads to less innovation relative to the intensity of the innovation activities. Conversely, less innovation activity in a framework based on relevant patterns of interactions could lead to more innovation output and productivity. Indeed, the absence of interaction both increases the convergence phase towards the value, but does not optimize it¹⁷. Hence, within the same enterprise it is possible to find significant activity with regard to knowing and creativity, but relatively lower innovative design and more strongly routinized organization.

Mathematically, the congestion phenomenon describes the non increasing relationship between the maximum technically feasible in some outputs and inputs (Färe and Svensson, 1980). Beside, Zhu (2000) asserts that an input x is congested if the relative slack $s_x^+ > 0$ (cf. Figure (2)). According to this point of view, the slack between the actual innovation capacity of the DMU under evaluation (at the point M in Figure (2)) and that of the postulated efficient DMU (at the point E in Figure (2)) can be used to measuring the relative degree of congestion.

Furthermore, the input excess can cause shortfall of productivity or decelerates the development of some innovation types. According to Tone and Sahoo (2004) and Kao (2010), these losses in outputs are due to the congestion effect. Vis-a-vis to the definition given by Färe and Svensson (1980), this last point of view on the congestion seems right. This form of loss is can be measured by $\beta = M_0F/M_0T$ (cf. Figure (2)).

In the Färe's literature (Färe et al., 1985, chap.4), η is the Farrell output measure of technical (in)efficiency, while β is described as the measure of loss of output due to lack of output disposability. In the same literature the measure $\phi = M_0F/M_0M = M_0F/M_0T \times M_0T/M_0M = \beta \times \eta$ is described as the weak output measure of technical efficiency. Kao (2010) well summarized all these points in his paper. This ϕ can be also obtained by the DEA-CCR model (Charnes et al., 1978). But here, if the congestion does not occur, we regard η as the shortfall of output due to the technical inefficiency. Else, if congestion occurs, η and β are regarded as the loss of output due to the congestion effect.

After deleting of β , another type of loss of output can occur as s_y^- . Here, we define the β as the common loss on the whole of outputs (common effect) due to the congestion in the whole of activities, while the s_y^- as the additional specific loss in each output if relative specific inputs are congested. Here, the MOLP-DEA model directly provides the extreme efficient projections and removes this type of slack (Lins et al., 2004) and β is regarded as the loss of the output y due to the congestion in the whole of activities.

Finally, X-efficiency can be evaluated by the illustrative distance iota ι between the point M under evaluation and the efficient projection point E (cf. Figure (2)), proposed by Leibenstein and Maital (1992). In the next section, we will see some technical problems in the use of iota. We then use instead the Russell graphical distance ρ , which we describe in the section (3.2), in its place.

¹⁷This is due to the lack of relevant feedback about experience, cross validations, explicit communication, as well as difficulties in the re-use knowledge and the selection of the good solutions. For example, the linear model of the designing process is seen as being weakly innovative since in this process, R&D pushes production and marketing without feedback paths (Kline and Rosenberg, 1986, p.286).

3. Measurement and Evaluation Models

3.1. Measurement of the innovation

Innovation intensity and innovation capacity are latent variables because they are not directly measurable (Hansen, 2001; Guan et al., 2006). Nevertheless, they can be measured by elementary categorical indicator variables of observed activities of the process and of observed achieved innovation types in the enterprise (Appendix A). These variables are categorized into five groups from of each an aggregate indicator is constructed. The first four aggregate indicators represent the innovation capacity. To evaluate the innovation capacity or innovation intensity in practice, we model each activity or each element of each innovation type by a random variable.

Now let us consider various tuples of indicator variables (in Appendix A, there are 9 tuples except TFP). Here, a tuple $x_i = (x_{i1}, x_{i2}, \dots, x_{ip_i})$ ¹⁸ defines a category i of p_i activities or an innovation type x_{ik} for $k = 1, \dots, p_i$ (see Grupp and Maital, 2001, p.9 for the same formulation). Clearly, each tuple is a discrete random vector. Then for $k = 1, \dots, p_i$ and for a DMU _{j} ¹⁹, let us pose:

$$x_{ik,j} = \begin{cases} 1 & \text{if } x_{ik} \text{ is observed at DMU}_j \\ 0 & \text{else} \end{cases} \quad (1)$$

If the indicator variable x_{ik} is ordered with l levels, it is decomposed into l new indicator variables. Then the l new variables are treated in the same way as in the formulation (1) taking into account the order of levels (cf. Banker and Morey, 1986). We aggregate the indicators $x_{ik,j}$ for the DMU _{j} as follows:

$$x_{ij} = \sum_{k=1}^{p_i} x_{ik,j} \quad (2)$$

If $x_{ij} = (x_{i1,j}, x_{i2,j}, \dots, x_{ip_i,j})$ are activities, we consider the variable x_{ij} as the intensity of activities of the DMU _{j} in the category i . But we use the normalized intensity index:

$$x_{ij} = \frac{1}{p_i} \sum_{k=1}^{p_i} x_{ik,j} \quad (3)$$

since it easily allows comparison of the intensity of activities of the same category of various DMUs in the same scale. Then x_{ij} ranges from 0 to 1. Hence, a DMU has a full innovation capacity whenever all intensities of its activities are equals to 1, i.e. if there are all activities in its process.

In contrast, the innovation intensity alone can group various innovation types (cf. Appendix A). For this variable, we take an interest in its entirety (cf. section (2)). Then, we modify the formulation (3) into (4) to aggregate all innovation types as follows:

$$y_j = \frac{1}{T} \sum_{j=1}^T \left[\frac{1}{p_i} \sum_{k=1}^{p_i} y_{ik,j} \right] \quad (4)$$

where T the number of innovation types and, p_i the number of indicator variables in each inno-

¹⁸We use x when we mean input and y for output.

¹⁹in the next, DMU means SME.

vation type i . Likely, innovation intensity ranges from 0 to 1. In conjunction with section (1), a DMU $_j$ is innovative whenever $y_j > 0$.

Obviously, the formulations (3) and (4) respectively provide a percentage of observed activities and a weighted percentage of observed innovation types. Then their use can be abusive because for example two DMUs can have the same innovation capacity according the formulation (3) but with different activities. In this case, the comparison could be wrong. Then to prevent this problem, one can introduce the use of a similarity index before any evaluation to grouping the similar DMUs on the activities (e.g. see [Deza and Deza, 2006](#), for the choice of similarity index).

Finally, we use the total factor productivity (TFP) as second output indicator of the innovation process. It is obtained using an index calculated from the financial data of individual enterprises. Data are available in Table (B.6)

3.2. Evaluation of the X-efficiency

Suppose there are n DMUs, each using m various inputs to produce s various outputs. Let $x = (x_1, \dots, x_m) \in \mathbb{R}_+^{n \times m}$ the inputs data matrix, $y = (y_1, \dots, y_s) \in \mathbb{R}_+^{n \times s}$ the outputs data matrix. Here, these data are obtained by the way outlined in section (3.1). Let us recall that in the context of innovation process, we compare the actual amount of TFP and innovation intensity of the DMU under evaluation with that maximally realizable among existing DMUs with similar activities. As mentioned in section (1), we use the DEA model to evaluate this difference. In their approach, i.e. the input-oriented model, [Leibenstein and Maital \(1992\)](#) suggested the use of the weighted euclidean iota ι to take into account all aspects of the X-inefficiency.

Here, we generalize this index taking into account both inputs and outputs dimensions at the graphical distance ρ of Russell, enhanced by [Pastor et al. \(1999\)](#). For a DMU $_0$, we present its Russell graph efficiency measure under VRS version:

$$\left\{ \begin{array}{l} \rho = \min \quad \frac{\frac{1}{m} \sum_{i=1}^m \theta_i}{\frac{1}{s} \sum_{r=1}^s \phi_r} \\ \text{s.t.} \quad \sum_{j=1}^n \lambda_j \cdot y_{rj} \geq \phi_r \cdot y_{rj_0}; \quad r = 1, \dots, s \\ \sum_{j=1}^n \lambda_j \cdot x_{ij} \leq \theta_i \cdot x_{ij_0}; \quad i = 1, \dots, m \\ \sum_{j=1}^n \lambda_j = 1 \\ \phi_r \geq 1, \theta_i \leq 1, \lambda_j \geq 0; \quad r = 1, \dots, s; i = 1, \dots, m; j = 1, \dots, n \end{array} \right. \quad (5)$$

where θ_i and ϕ_r are the efficiency components respectively in inputs and in outputs, λ_j the coefficients of convex combination of the efficient peers units for the DMU $_0$ under evaluation. This index satisfies some properties of an efficiency measure ([Färe and Lovell, 1978](#); [Pastor et al., 1999](#)). In their work, [Pastor et al. \(1999\)](#) gave the computational technique of this index. It should also be noted that the computational technique proposed by these authors seeks to find a unique efficient projection by minimizing the above ratio.

The MOLP-DEA approach suggests a set of efficient projections among them we can choose the nearest with respect to the distance defined by the objectives of the DMU under evaluation (Lins et al., 2004). Then, we use the MOLP-DEA to obtain θ_i and ϕ_r and, ρ results therefrom. Through this model, we also evaluate the components of the X-inefficiency such as technical inefficiency and congestion (congestion effect and the degree of congestion). These elements determine the potential internal sources of X-inefficiency for each DMU. The MOLP-DEA model, defined in program (6), derives from the BCC output oriented model (Banker et al., 1984; Lins et al., 2004) as follows:

$$\left\{ \begin{array}{l} \max \quad (\phi_1, \dots, \phi_s) \\ \text{s.t.} \quad \sum_{j=1}^n \lambda_j \cdot y_{rj} \geq \phi_r \cdot y_{rj_0}; \quad r = 1, \dots, s \\ \sum_{j=1}^n \lambda_j \cdot x_{ij} \leq x_{ij_0}; \quad i = 1, \dots, m \\ \sum_{j=1}^n \lambda_j = 1 \\ \phi_r \geq 1, \lambda_j \geq 0; \quad r = 1, \dots, s; j = 1, \dots, n \end{array} \right. \quad (6)$$

where (ϕ_1, \dots, ϕ_s) are the weak output measures of technical efficiency. The program (6) can be solved by various methods to find all non dominated solutions (ϕ_1, \dots, ϕ_s) with the optimal value of $(\lambda_1, \dots, \lambda_n)$. For example Zeleny (1974) has provided a complete dissertation with some computational techniques for solving a such program. Let us note that MOLP-DEA and variant classical models, such as radial, additive or slack based models, provide the same efficient frontier but not the same efficient projection for each inefficient DMU (Hosseinzadeh Lotfi et al., 2009).

Here like the classical models, the MOLP-DEA is computed in two stages. First it is to perform $(\phi, \lambda) = (\phi_1, \dots, \phi_s, \lambda_1, \dots, \lambda_n)$. Secondly one evaluates the slack variables s_r^- (loss of output r) and s_i^+ (excess of input i) with new $\tilde{\lambda}_j$ by maximizing the second objective function $(\sum_{r=1}^s s_r^- + \sum_{i=1}^m s_i^+)$ by using the optimal value ϕ_r^* obtained from the first stage as follows:

$$\left\{ \begin{array}{l} \max \quad (\sum_{r=1}^s s_r^- + \sum_{i=1}^m s_i^+) \\ \text{s.t.} \quad \sum_{j=1}^n \tilde{\lambda}_j \cdot y_{rj} - s_r^- = \phi_r^* \cdot y_{rj_0}; \quad r = 1, \dots, s \\ \sum_{j=1}^n \tilde{\lambda}_j \cdot x_{ij} + s_i^+ = x_{ij_0}; \quad i = 1, \dots, m \\ \sum_{j=1}^n \tilde{\lambda}_j = 1 \\ s_i^+, \tilde{\lambda}_j \geq 0; \quad i = 1, \dots, m; j = 1, \dots, n \end{array} \right. \quad (7)$$

For a DMU₀ under evaluation, the possible efficient projections are determined by the coordinates:

$$\left\{ \begin{array}{l} \hat{x}_{ij_0} = x_{ij_0} - s_i^+; \quad i = 1, \dots, m \\ \hat{y}_{rj_0} = \phi_r \cdot y_{rj_0} + s_r^-; \quad r = 1, \dots, s \end{array} \right. \quad (8)$$

Let $Eff(j_0)$ be the set of its possible efficient projections from the MOLP-DEA for the DMU₀. Now, we must to choose an efficient projection in $Eff(j_0)$. Assume that for this DMU₀ there

are two vectors of weights $\mu = (\mu_1, \dots, \mu_m)$ and $\nu = (\nu_1, \dots, \nu_s)$ respectively assigned to the activities and the results. Let $\delta^{\mu, \nu}$ be a distance defined according to μ and ν (e.g. see [Deza and Deza, 2006](#), for the choice of distance). Then, we define the objective efficient projection or the most preferred solution (MPS, cf. [Yang et al., 2009](#)) for the DMU_0 by:

$$DMU_0^* = \arg \min_{DMU \in Eff(j_0)} \delta^{\mu, \nu}(DMU_0, DMU) \quad (9)$$

And then we define previous θ_i and ϕ_r in the program (5) as follows:

$$\begin{cases} \theta_i = \frac{x_{ij_0}^*}{x_{ij_0}}; & i = 1, \dots, m \\ \phi_r = \frac{y_{rj_0}^*}{y_{rj_0}}; & r = 1, \dots, s \end{cases} \quad (10)$$

Clearly the DMU under evaluation is X-efficient whenever $\rho = 1$, i.e. $\theta_i = \phi_r = 1$ or equivalently $\phi_r = 1$ and $s_i^+ = 0$; else it is X-inefficient. Each $(1 - 1/\phi_r)$ globally measures the shortfall in each output and each $(1 - \theta_i)$ measures the possible contraction in each input. Practically, we may regard $(1 - \theta_i)$ as the sufficient level of activities to avoid the obstruction of others activities of the process (principle of parsimonious). Now we decompose each ϕ_r in order to determine whether the losses are due to a simple technical inefficiency or/and a congestion effect.

In section (2), we have clarified that X-inefficiency can appear as technical form, congestion forms or both. Here the congestion effect causes the loss of output at $(1 - 1/\beta_r)$, while the technical inefficiency causes the loss of output at $(1 - 1/\eta_r)$ (cf. section (2)). [Tone and Sahoo \(2004\)](#) have developed a linear program model to obtain a radial η . But their model only detects the weak form of the congestion effect as mentioned [Sueyoshi and Sekitani \(2009\)](#). These last authors have enhanced and extended the Tone-Sahoo model in the multiple optimal projection cases in order to detect the strong form of the congestion effect. Here, we use this last model to compute the multiple η_r , formulated in program (11) as follows:

$$\left\{ \begin{array}{l} \max \quad (\eta_1, \dots, \eta_s) \\ \text{s.t.} \quad \sum_{j=1}^n \zeta_j \cdot y_{rj} \geq \eta_r \cdot y_{rj_0}; \quad r = 1, \dots, s \\ \sum_{j=1}^n \zeta_j \cdot x_{ij} = x_{ij_0}; \quad i = 1, \dots, m \\ \sum_{j=1}^n \zeta_j = 1 \\ \eta_r \leq \phi_r; \quad r = 1, \dots, s \\ \eta_r \geq 1, \zeta_j \geq 0; \quad r = 1, \dots, s; j = 1, \dots, n \end{array} \right. \quad (11)$$

Here ϕ_r are provided from the formulation (10). When the DMU is in the congested area (cf. Figure (2)), clearly we have $\eta_r \leq \phi_r$ for all $r = 1, \dots, s$. As seen in section (2), we decompose the weak output measure of technical efficiency ϕ_r by separating the technical inefficiency η_r from congestion effect β_r by the following relation $\phi_r = \beta_r \times \eta_r$ ([Tone and Sahoo, 2004](#); [Kao, 2010](#)). This distinction allows us to know whether an inefficient DMU suffers more from the congestion effect than the technical inefficiency. The program (11) is the same that the program (6) except for the input constraints. The technical inefficiency η_r (or $1 - 1/\eta_r$) is

the shortfall in outputs due to the failure of interaction between activities. The index β_r (or $1 - 1/\beta_r$) is the shortfall in outputs due to the absence of interaction between activities useless, following the fruitless increase of inputs (Färe and Svensson, 1980). For a group J of DMUs, this useless increase of activities, defined as the measure of the congestion rate or of the degree of congestion (Zhu, 2000), can be measured as follows:

$$\tau_i(J) = \frac{\sum_J s_i^+(J)}{\sum_J x_i(J)} \quad (12)$$

where $s_i^+(J)$ are the slacks in input i provided in program (6) for this group J . This quantity enables us to appreciate the rate of under-utilization of innovation capacity in this category of activities.

4. Empirical analysis

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 (10-20), from 20 to 50 employees (20-50), more than 50 employees (50-250); (b) the level of sector technology (LST) divided into three categories as lower technology (LT), Medium lower technology (MLT), medium high technology (MHT) (cf. Table (4)).

The data are gathered through interviews with the entrepreneurs using a set of questions (Gaussens, 2009) relating to the strategies and processes of the enterprise. The questions deal with the innovation strategy and innovation process that the entrepreneur followed from 2006 to 2008. In Table (2), we present the empirical distribution of the innovation capacity and the outcomes of innovation processes.

Table 2:
Descriptive statistics on the indicators.

Indicators	Min	Mean	Max	S.D.*
Outputs of innovation process				
Innovation intensity (y_1)	0.03	0.28	0.80	0.18
Total factor productivity (y_2)	7.81	21.44	40.6	7.83
Innovation capacity				
Designing capacity (x_1)	0.08	0.30	0.67	0.13
Organizational learning capacity (x_2)	0.16	0.52	0.88	0.19
Knowing capacity (x_3)	0.04	0.23	0.48	0.10
Creativity capacity (x_4)	0.01	0.33	0.65	0.15

*Standard deviation.

The empirical results are summarized in Table (4). Firstly, our estimations show the relative importance of X-inefficiency in the innovation processes of SMEs. About 71.25% of innovation processes are X-inefficient. In addition:

- (a) Neither the technological level of the sector nor the firm size is determinants of X-efficiency (respective significance levels with respect to the Mann-Whitney tests: 0.2285 and 0.8887).

- (b) In average, the X-inefficiency causes both about 13% of loss of productivity and 33% of loss of innovation intensity. In particular, the only congestion causes about 22% of loss of innovation intensity.
- (c) Inefficiency in the innovation process appears most frequently as a congestion problem (significance level with respect to the Wilcoxon signed rank test for $\bar{\eta}_1 > \bar{\beta}_1$: 0.0510). In addition we observe non-zero rate of congestion in 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 exploitation and exploration activities (respectively 20.04% and 20.19% following the formulation (12)). Creativity capacity and 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 designing and 12.6% in knowing following the formulation (12)).

Secondly, this study enabled 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 (significance level with respect to the Mann-Whitney test: 0.0267). However in innovation intensity, the difference in level is not significant (significance level with respect to the Mann-Whitney test: 0.4522).
- (b) On average, inefficiency is significantly characterized more by a lack of innovation intensity than by a lack of productivity (cf. Table (4)):
- $\bar{\phi}_2 > \bar{\phi}_1$, (*p.value* = 0.0005)
 - $\bar{\eta}_2 > \bar{\eta}_1$, (*p.value* = 0.0808)
 - $\bar{\beta}_2 > \bar{\beta}_1$, (*p.value* = 0.0005)

Table 4:
Average score results.

Categories	F./C.*	$\bar{\rho}$	$\bar{\phi}_2$	$\bar{\phi}_1$	$\bar{\eta}_2$	$\bar{\eta}_1$	$\bar{\beta}_2$	$\bar{\beta}_1$
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 – 250	13	0.55	0.78	0.64	0.89	0.79	0.89	0.82
LST								
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

*Number of firms per category.

5. Characterization of X-inefficiency

In this section, we describe the main characteristics of X-inefficiency for the SMEs. Then we use two exploratory techniques such as the induction tree using the recursive partitioning (Izenman, 2008, p.281-313) and the multiple correspondence analysis (Izenman, 2008, p.658-663).

The first approach is to identify the congestion factor in the activities. The latter allows to reveal the nature of the association of activities generating the congestion to be highlighted. The exploratory analysis furthers our understanding of the congestion phenomenon, which has been quantified previously. The Table (B.6) describes the congested activities (cf. [Appendix B](#)).

This outcome suggests that the X-inefficiency of innovation processes in the enterprises is well characterized by the lack of integration in the exploration activities of the designing and learning process. They reveal interaction failures between on one hand the exploration activities of the implementers and the knowledge of external actors, and on the other hand, exploitation activities in the enterprise. It results in an under-exploitation of knowledge and experience of both implementers and external actors, which translates into less productive strategic deployment, feedback about experience, knowledge capitalization, selection of new solutions and external training. Indeed, the interaction failures between drivers and implementers or external actors in the process result in the lack of reliable feedback which weakens both the relevance of goals²⁰ and the fact that they could be called into question - and the relevance of assessment of rules, standards, procedures or routines. Conversely, the interaction's failures between designing and using leads both to highly confused strategic intent - in terms of opportunity to create value - and to difficulties to in selecting the new solutions. This does not enable the actors in the innovation process both to either develop reciprocal knowledge or mutual understanding and to nor motivate themselves to explore in relevant areas.

6. Conclusion

This paper makes two contributions. Firstly we developed the concept of X-efficiency from the works of [Leibenstein](#) (1968, 1969, 1979) and adapted it to our proposed model of the innovation process. We have specified each component of X-inefficiency and their appropriate measure.

Secondly, we suggested the use of the combination of some efficiency measurement models such as both the multiobjective DEA and the Russell graph efficiency measure, to evaluate the global X-inefficiency of innovation process. The Russell graph approach enabled difficulties related to the index based on the proximity introduced by [Leibenstein and Maital](#) (1992) to be overcome. Here, the DEA model has made a good contribution to highlighting the difficulties that the majority of entrepreneurs have in managing their innovation processes and identifying the internal sources of X-inefficiency.

From an X-inefficiency analysis based on interaction failure between exploitation and exploration, we show that the X-inefficiency of the innovation processes mainly assumes the congestion form as the fundamental source of under-utilization of innovation capacity. In particular, this involves organizational learning and creativity. This result is discussed as the non-implementation by the entrepreneur of efficient rules or standards of interaction in certain areas of the collective design of the business.

Beyond a simple approach that explains productivity directly by innovation intensity, our approach suggests that innovation process efficiency may account for greater productivity, and that higher innovation intensity could explain higher efficiency through a learning effect. Finally, higher productivity could explain higher innovation intensity through a self-selection

²⁰In terms of ability to achieve value.

effect. Further work will need to develop these lines of research and to achieve a more realistic approach to process innovation in SMEs.

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Appendix A. Description of indicators

Designing activities

- Design methods (12 items)
- Designing scope (11 items)
- Market needs identification (7 items)
- Products and methods description (20 items)
- Change and areas of exploration (11 items)
- Selection of solutions (28 items)
- Risk management (5 items)
- Project management (4 items)
- Human resources management (1 item)

Organizational learning activities

- Learning scope (9 items)
- Feedbacks about experiments (3 items)
- Experimentations with new situations (5 items)
- Strategic deployment (2 items)
- Routines (6 items)
- Working group on problem solving methods (1 item)

Knowing activities

- Knowing scope (7 items)
- Internal production of knowledge (11 items)

- External sources of knowledge (36 items)
- Risk management (1 item)
- Knowledge community management (13 items)
- Funding research (1 item)
- Human resources management (4 items)

Creativity activities

- Creativity tools (7 items)
- Search for new solutions (9 items)
- Team management (5 items)

Innovation types (innovation intensity)

- Product innovation achieved (2 items)
- Process innovation achieved (4 items)
- Marketing innovation achieved (5 items)
- Organization innovation achieved (5 items)
- Other indicators of innovation intensity (6 items)

Total factor productivity TFP (see [Grupp and Maital, 2001](#), p.136 for the model used)

$$TFP = VA / (L^\alpha \cdot K^{1-\alpha})$$

- VA : overall value added
- L : number of employees
- K : capital
- α : fraction of value added attributable to labor L

Appendix B. Data and Results

Table B.6:
Data (cf. section
(3.1))

DMUs	Size	LST	x_1	x_2	x_3	x_4	y_1	y_2
DMU1	10-20	MLT	0.233645	0.413333	0.234043	0.434783	0.296667	20.15088
DMU2	10-20	LT	0.252336	0.5	0.138298	0.246377	0.374167	9.122024
DMU3	20-50	MLT	0.299065	0.646667	0.308511	0.304348	0.163333	32.20427
DMU4	20-50	LT	0.350467	0.6	0.234043	0.478261	0.05	29.42137
DMU5	10-20	MLT	0.285047	0.42	0.212766	0.376812	0.083333	18.74451
DMU6	10-20	MHT	0.084112	0.34	0.159574	0.26087	0.133333	27.90674
DMU7	10-20	LT	0.140187	0.54	0.117021	0.26087	0.116667	24.76689
DMU8	10-20	LT	0.406542	0.68	0.255319	0.449275	0.323333	17.0134
DMU9	10-20	MLT	0.598131	0.806667	0.276596	0.434783	0.54	23.06452
DMU10	20-50	MLT	0.299065	0.48	0.117021	0.173913	0.033333	20.44085
DMU11	50-250	LT	0.38785	0.866667	0.361702	0.507246	0.216667	20.74532
DMU12	20-50	LT	0.121495	0.34	0.234043	0.144928	0.433333	10.51551
DMU13	20-50	MLT	0.397196	0.713333	0.276596	0.376812	0.803	17.91828
DMU14	20-50	MLT	0.331776	0.7	0.457447	0.463768	0.267667	23.08244
DMU15	10-20	LT	0.32243	0.72	0.308511	0.536232	0.218667	34.9729
DMU16	10-20	MLT	0.28972	0.286667	0.202128	0.173913	0.5	15.16544
DMU17	10-20	MLT	0.317757	0.486667	0.212766	0.130435	0.066667	19.48062
DMU18	10-20	LT	0.130841	0.4	0.148936	0.231884	0.1	17.48999
DMU19	10-20	MLT	0.308411	0.48	0.095745	0.173913	0.47	23.29662
DMU20	50-250	LT	0.364486	0.64	0.319149	0.521739	0.333333	16.04297
DMU21	20-50	LT	0.345794	0.52	0.265957	0.333333	0.725	16.37239
DMU22	10-20	LT	0.345794	0.46	0.244681	0.449275	0.09	10.471
DMU23	50-250	LT	0.668224	0.82	0.404255	0.652174	0.59	25.38181
DMU24	20-50	MHT	0.228972	0.506667	0.244681	0.304348	0.39	30.52528
DMU25	10-20	LT	0.457944	0.686667	0.234043	0.434783	0.156667	12.121
DMU26	10-20	MHT	0.182243	0.4	0.191489	0.188406	0.306667	31.52042
DMU27	10-20	MHT	0.64486	0.806667	0.478723	0.449275	0.441333	15.28894
DMU28	50-250	MLT	0.299065	0.626667	0.223404	0.507246	0.386667	11.70599
DMU29	20-50	MHT	0.11215	0.38	0.202128	0.188406	0.033333	27.88146
DMU30	10-20	MHT	0.205607	0.4	0.117021	0.391304	0.233333	31.56297
DMU31	20-50	MLT	0.46729	0.74	0.351064	0.565217	0.35	33.32272
DMU32	20-50	MHT	0.32243	0.68	0.297872	0.478261	0.22	19.57947
DMU33	10-20	MLT	0.102804	0.38	0.117021	0.101449	0.133333	15.65946
DMU34	10-20	LT	0.425234	0.66	0.37234	0.608696	0.53	13.56422
DMU35	20-50	LT	0.336449	0.34	0.319149	0.362319	0.216667	11.18972
DMU36	20-50	LT	0.415888	0.566667	0.265957	0.434783	0.463333	21.68926
DMU37	10-20	MHT	0.247664	0.72	0.276596	0.217391	0.283333	27.72829
DMU38	10-20	LT	0.266355	0.38	0.234043	0.376812	0.340333	17.62008
DMU39	10-20	MLT	0.317757	0.713333	0.265957	0.434783	0.35	33.77195
DMU40	10-20	MHT	0.17757	0.406667	0.170213	0.347826	0.033333	21.62289
DMU41	20-50	LT	0.182243	0.353333	0.276596	0.246377	0.033333	13.4196
DMU42	10-20	LT	0.266355	0.34	0.180851	0.144928	0.336667	11.37296
DMU43	20-50	LT	0.242991	0.513333	0.180851	0.188406	0.25	32.20955
DMU44	50-250	MHT	0.453271	0.78	0.287234	0.507246	0.216667	27.97397
DMU45	10-20	MHT	0.172897	0.42	0.234043	0.188406	0.25	35.104
DMU46	20-50	LT	0.457944	0.726667	0.404255	0.565217	0.38	7.806869
DMU47	50-250	MLT	0.509346	0.7	0.329787	0.478261	0.35	12.52348
DMU48	20-50	MHT	0.448598	0.88	0.382979	0.608696	0.325	36.61813
DMU49	20-50	MLT	0.196262	0.54	0.159574	0.376812	0.033333	17.99318
DMU50	10-20	MLT	0.364486	0.8	0.319149	0.565217	0.133333	14.82769
DMU51	50-250	MLT	0.28972	0.526667	0.223404	0.333333	0.073333	29.31872
DMU52	20-50	LT	0.242991	0.653333	0.138298	0.333333	0.05	28.99701
DMU53	10-20	LT	0.186916	0.593333	0.202128	0.246377	0.266667	22.25605
DMU54	20-50	LT	0.373832	0.58	0.244681	0.376812	0.233333	20.47581
DMU55	20-50	MLT	0.261682	0.5	0.297872	0.202899	0.133333	30.20745
DMU56	20-50	LT	0.504673	0.486667	0.117021	0.434783	0.491667	9.751816
DMU57	50-250	MLT	0.588785	0.766667	0.37234	0.565217	0.296667	40.60486
DMU58	10-20	LT	0.369159	0.733333	0.148936	0.347826	0.483333	14.21128
DMU59	20-50	MHT	0.271028	0.186667	0.180851	0.217391	0.52	30.13628
DMU60	20-50	MHT	0.205607	0.26	0.117021	0.347826	0.2	28.72511
DMU61	20-50	LT	0.168224	0.32	0.095745	0.043478	0.263333	20.67349
DMU62	10-20	LT	0.168224	0.193333	0.106383	0.289855	0.1	12.71614
DMU63	10-20	LT	0.093458	0.2	0.138298	0.217391	0.133333	24.7181
DMU64	20-50	LT	0.149533	0.22	0.148936	0.217391	0.253333	20.29313
DMU65	10-20	LT	0.116822	0.34	0.042553	0.014493	0.233333	12.23708
DMU66	20-50	LT	0.102804	0.16	0.095745	0.231884	0.133333	22.93501
DMU67	10-20	MLT	0.228972	0.16	0.106383	0.144928	0.223333	21.38706
DMU68	10-20	MLT	0.168224	0.42	0.319149	0.289855	0.15	14.20517
DMU69	20-50	MHT	0.17757	0.206667	0.223404	0.202899	0.2	19.99794
DMU70	20-50	MLT	0.17757	0.593333	0.255319	0.217391	0.216667	23.33706
DMU71	10-20	MHT	0.196262	0.566667	0.244681	0.202899	0.37	28.74251
DMU72	20-50	MHT	0.280374	0.466667	0.244681	0.202899	0.233333	13.63692
DMU73	20-50	MHT	0.224299	0.36	0.042553	0.289855	0.133333	27.83975
DMU74	10-20	LT	0.257009	0.666667	0.329787	0.231884	0.396667	9.502229
DMU75	50-250	LT	0.308411	0.52	0.255319	0.26087	0.35	18.55242
DMU76	20-50	MHT	0.411215	0.653333	0.202128	0.391304	0.1	30.14269
DMU77	50-250	MLT	0.149533	0.38	0.148936	0.086957	0.133333	24.00772
DMU78	50-250	LT	0.439252	0.573333	0.329787	0.333333	0.719667	26.50729
DMU79	50-250	MLT	0.261682	0.333333	0.12766	0.202899	0.216667	20.0725
DMU80	50-250	MLT	0.537383	0.78	0.404255	0.42029	0.703333	8.711451

Table B.9:

Characterizations of the X-inefficiency by the congested activities

Area of activities	Category of activities	Sub-category of activities	Elementary activities (items)
Exploitation	Designing	Selection of the solutions	Critical analysis of the new solutions—from tests for new products and methods of manufacturing
		Organizational learning	Learning scope
		Feedbacks about experience	Calling into question objectives
		The strategic deployment	Setting targets
		Routines	The definition and the evaluation of routines
Exploration	Knowing	Knowledge community management	Group and team work
		External sources of knowledge	The quest for knowledge from outside sources within informal networks
	Creativity	Creativity tools	Development of their own creativity
		Search of new solutions	Development and search of new solutions
			Encouraging of implementers to seek other solutions
		Team management	

Cf. [Appendix A](#) for the categories and the sub-categories.

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