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Measuring and benchmarking productive systems performances using DEA: an industrial case

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Abstract. The study presents a comprehensive analysis of the efficiency over time of five steel plants pertaining to one of the largest private groups in Italy. In particular, the paper proposes a new technique for plant performance measurement that is able to help the management in formulating manufacturing strategies according to the performance measurements usually available in industrial environments. The analysis is carried out by the methodology of Data Envelopment Analysis (DEA),

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taking advantage of several improved solutions proposed in the literature adopted to augment the discriminating resolution. Results obtained are summed up by means of suitable cluster analysis. Finally, thanks to the dual formulation of DEA, a technical and economic analysis is proposed with reference to the productive units identified as inefficient. The technique proposed was successfully applied to the industrial case of reference and it can be easily extended to every manufacturing context.

1. Introduction

Comparing the performance of competitive manufacturing systems is a complex task which requires the resolution of a multifaceted problem. The main reasons for the complexity of plant benchmarking are (i) the coexistence of several conflicting performance criteria and (ii) the wide variety of available evaluation criteria. In this paper, thanks to the utilization of several suitable performance parameters, the Data Envelopment Analysis (DEA) technique is used to rank the relative efficiency of five productive units of a large private company with reference to the years from 1995 to 1997.

By adopting the DEA approach for plant performance measurement, it is possible (i) to consider several manufacturing performance dimensions in an integrated and comparative manner, (ii) recognizing the causes of gaps in inefficient plants so as to suggest new manufacturing strategies for restoring competitive levels and (iii) quantifying the need for improvement in order to reach efficiency. In other words, the method here proposed can represent a powerful and interesting tool of analysis for feasibility studies concerning the definition of future manufacturing investment strategies. It is particularly helpful in defining the opportune areas for intervention (i.e. a reduction in scraps rather than an improvement in manpower productivity). It is evident that being able to identify the ‘true’ aspects of inefficiency in a complex network of productive units helps the management in defining the most opportune and appropriate strategy for the production, planning and control (PP&C) systems and/or methodologies. Once adopted, these strategies will permit the productive units to maintain a satisfactory competitive level.

Initially, the DEA is applied in its traditional form. In sections 6–8, three different approaches are used to improve DEA discriminating power (reduction of factors, cross-efficiency and stepwise approach). Finally, results are ranked by cluster analysis, thus focusing on analogies or discrepancies of the performance values evaluated by the different DEA methods. The cluster analysis also allows the evaluation of each single plant performance over the successive time periods (1995–1997). As usual in linear programming (LP) problems, the dual form of the DEA technique enables the analysis of improvement possibilities for each plant, highlighting the critical parameters to be modified in order to increase the relative performance of the plant in question.

2. Data Envelopment Analysis (DEA)

DEA is an LP-based technique proposed by Charnes *et al.* (1978) which evaluates the relative efficiency of several Decision-making Units (DMUs) by considering multiple inputs (i.e. resources used) and outputs (i.e. products and/or performances obtained). The efficiency is defined as the ratio of the weighted sum of the m outputs to the weighted sum of the n inputs, i.e.:

$$\text{Efficiency of DMU } j = E_j = \frac{\text{weighted sum of outputs}}{\text{weighted sum of inputs}} = \frac{\alpha_1 y_{1j} + \cdots + \alpha_m y_{mj}}{\beta_1 x_{1j} + \cdots + \beta_n x_{nj}}$$

where:

α_k is the weight of output k
β_k is the weight of input k
y_{kj} is the amount of output k from DMU j
x_{kj} is the amount of input k from DMU j

The efficiency is a value usually constrained to the interval $[0, 1]$. The evaluation of the efficiency of each DMU (e.g. a productive unit) requires the definition of a single and common set of weights for each plant, thus introducing the problem of *how* this set can be obtained. The case proposed considers a DMU as an alternative manufacturing system and several possible performance criteria can be considered as input or output: each plant was intended to satisfy only one or a few managerial requirements. For example, one plant may reflect the strategic need for a flexible production and this target is reached to the detriment of a high number of set-ups and machine idle times. Consequently, the performances of the different criteria adopted may legitimately differ from plant to plant and, as such, may be assigned different relevance (weights).

Once the impossibility of finding a common set of weights has been recognized, a possible approach is to adopt the set of weights most favourable to each plant, with respect to competing plants.

Considering a set of n competing manufacturing systems, the relative efficiency E_j of plant j $(j = 1, \ldots, s)$ can be evaluated by the resolution of the following model:

$$\max E_j \tag{1}$$

subject to

$$\frac{\sum_{k=1}^{m}\alpha_k y_{kj}}{\sum_{i=1}^{n}\beta_i x_{ij}} \leq 1 \quad \text{for each DMU } j = 1, \ldots, s \quad \text{(i)}$$

$$\alpha_k \geq 0 \qquad k = 1, \ldots, m \qquad \text{(ii)}$$

$$\beta_i \geq 0 \qquad i = 1, \ldots, n \qquad \text{(iii)}$$

Constraints (ii) and (iii) impose a positive value on the weights of inputs and outputs (i.e. the variables of the model). Constraint (i) obliges the relative efficiency of each plant to be lower than or equal to the maximum unitary value. Therefore, the solution obtained from model (1) produces the set of weights *most favourable* to plant j, with respect to the other plants, and the E_j value obtained represents the maximum relative efficiency obtainable. It is also evident that the overall performance of the entire set of plants requires the resolution of a model focusing on each plant in turn. As the cost function may vary from problem to problem, weights obtained for each plant may be different. Model (1) is fractional LP, but it can be easily transformed into an LP one, as in Charnes *et al.* (1978):

$$\max H_j = \sum_{k=1}^{m}\alpha_k y_{kj} \tag{2}$$

subject to

$$\sum_{i=1}^{n}\beta_i x_{ij} = 1 \qquad \text{(i)}$$

$$\sum_{k=1}^{m}\alpha_k y_{kj} - \sum_{i=1}^{n}\beta_i x_{ij} \leq 0 \quad \text{for each DMU } j = 1, \ldots, s \quad \text{(ii)}$$

$$\alpha_k \geq 0 \qquad k = 1, \ldots, m \qquad \text{(iii)}$$

$$\beta_i \geq 0 \qquad i = 1, \ldots, n \qquad \text{(iv)}$$

In fact, model (1) can be solved as an LP by setting its denominator equal to some arbitrary constant and maximizing its numerator. The LP (2), or its dual version, is commonly adopted in DEA applications reported in the literature.

As a benchmarking approach, DEA has been proposed in numerous different applications: banks, hospitals, schools, technology selection, university departments, no-profit organizations, etc. An excellent bibliography is reported in Seiford (1996). In terms of performance evaluation of production systems, we can recall the studies of Ross and Droge (2002) (distribution centres), Bowlin (1987) and Clarke (1992) (maintenance activities), Ross *et al.* (1998) (supply chain), Kleinsorge *et al.* (1989) (logistics), Ito *et al.* (1999) (resource allocation), Parkan (1991) (operational performance), Ray and Kim (1995) (production cost efficiency), and Schefczyk (1993) (industrial production performances).

It is evident that several applications of DEA concerning different production efficiency aspects have already been proposed in the literature. Nevertheless, they:

- have not considered the efficiency of production systems in terms of technical and operative factors as wide as this study;
- have not considered a wide range of factors in the model (section 4);
- have often neglected the problem of the discrimination power of the DEAs (sections 6–8);
- rarely use the dual analysis of the DEA (section 10).

The following sections will highlight the contribution of the present study in these fields. Moreover, it proposes the utilization of cluster analysis with the aim of reassuming and better estimating the various results (ranking of efficiency) with different methodologies (section 9). In this way, a more comprehensible and stable final result of the analyses is presented.

3. The company profile

The company considered in the present study controls more than 50 companies, with a consolidated turnover of about 1.5 billion euros and 3,000 employees, working in Italy and abroad in various manufacturing fields. The core business is the production and sale of stainless and carbon steels. About 40 productive units are located in Italy and abroad, for a total yearly production of more than 1,600,000 tons of steel, including 900,000 tons of pipes (the largest fraction refers to welded pipes, about one-third is dedicated to the production of coils, sheets and bars, both hot and cold machined). Customers are internationally distributed: the flexible production and the extensive distribution system allow the company to meet the requirements of even small enterprises.

4. Data selection

As mentioned before, DEA analysis is applied to the five productive units of the primary company (here defined as A, B, C, D and E) which represent its core business. The analysis refers to three years: 1995, 1996 and 1997. The time interval considered has been set according to the convenience of the company, together with the availability of data. Seventeen different variables are identified as possible performance factors: twelve of them are considered as outputs and five as inputs.

Outputs

(1) Produced quantity, expressed in tons per year.
(2) Scrapped quantity, expressed in tons per year.
(3) Operating index: represents the availability of the plant for production, expressed as a percentage. It can be calculated as the ratio between the operating time (both plant and personnel available for production needs) and the calendar time (given a plant with several productive lines, it can be expressed, for example, as the number of hours per month that the plant is open multiplied by the number of productive lines).
(4) Idle time: represents the time associated with unexpected breaks in production, because of breakdowns, although the personnel are ready for production.
(5) Utilization index: takes into account the time for which the plant is strictly devoted to production. It can be formulated as the ratio between the productive time (both personnel and plant carry out production tasks) and the operating time.
(6) Man-worked hours: represents the percentage of man-worked hours, calculated with reference to the entire amount of available hours (normal and overtime).
(7) Actual plant productivity: expresses the ratio between the produced quantity and the number of operating hours of the plant.
(8) Actual worker productivity: expresses the ratio between the produced quantity and the number of man-worked hours.
(9) Raw material stocks.
(10) Work-in-process (WIP).
(11) Finished product stock.
(12) Absenteeism (%).

Inputs

(13) Number of employees: includes both direct and indirect manpower.
(14) Average cost per employee: represents the expenditure for salaries per year.
(15) Overtime (hours per year).
(16) Number of staff personnel (not directly involved in production activities).
(17) Investments.

Investments considered include the years 1993–1994, too, because of their effect on the performance of the years that follow. In fact, the effects of investments require an opportune interval of time before showing their effects: we have estimated that there exists a correlation between the amount produced in one year and the economic resources allocated in different successive years.

The choice of the produced amount as second variable of correlation is based on the main investments of the company: the largest part of the group investments are devoted to increasing both production capacity and production rates. According to the data of the five productive units, the strongest correlation is obtained by considering a link between the produced quantity of a specified year and the investments made two years in advance: this concept will also be adopted to evaluate the relative efficiency of a single plant.

Normalized indices for the five productive units in three different years are offered in table 1. In some cases, normalization has been carried out on the reciprocal of the value (e.g. scrapped quantity, as it is to be kept as low as possible).

5. The standard DEA application

The application of the traditional DEA model (2) to the group data for the 15 productive units leads to the results shown in table 2. It is evident that an excessive number of productive units reach maximum efficiency, thus making the analysis in question useless. The discriminatory power of the final ranking generally represents the main limit of DEA. The total weight flexibility characterizing the LP (2) allows a high proportion of plants to reach the maximum (or near maximum) value of overall performance: this is due to the fact that the LP (2) states that every criterion has a positive weight. Consequently, a criterion can be ignored in the final assessment and, frequently, productive units reach the maximum value of *relative* efficiency only in virtue of an optimized set of weights characterized by some other values equal to zero. However, the generic weight can be interpreted as a value of the importance that the DMU target assigns to the corresponding input or output: assigning 'zero importance' to a criterion represents an unrealistic choice. In this case, 'false' efficiency is detected (Baker and Talluri 1997). Various solutions have been proposed to resolve this problem:

(1) Whenever possible, a number of plants which is almost twice the number of inputs and outputs adopted is to be tested (Bowlin 1987). Thus, the number of DEA degrees of freedom is reduced: it is important to reduce the number of factors introduced in the efficiency evaluation by also evaluating the eventual correlation between different criteria (Kim and Hendry 1998).
(2) For each plant, the corresponding cross-efficiency can be calculated, in place of the conventional 'simple' efficiency (Doyle and Green 1994).

Table 1. Numerical data (monetary flows considered as absolute values, without inflation).

	A95	A96	A97	B95	B96	B97	C95	C96	C97	D95	D96	D97	E95	E96	E97
Output															
Produced quantity	1	0.854	0.977	0.064	0.071	0.084	0.080	0.114	0.168	0.107	0.100	0.126	0.288	0.313	0.349
Scrapped quantity	0.126	0.198	0	0.951	0.933	0.914	0.931	0.893	0.829	0.902	0.907	0.871	0.750	0.706	0.643
Operating index	1	0.945	0.996	0.648	0.700	0.764	0.241	0.232	0.348	0.744	0.560	0.687	0.672	0.739	0.731
Idle time	0.249	0.094	0	0.851	0.961	0.960	0.976	0.985	0.969	0.832	0.826	0.821	0.789	0.704	0.704
Utilization index	0.972	0.958	0.961	1	0.994	0.998	0.937	0.973	0.947	0.906	0.853	0.857	0.771	0.739	0.734
Actual plant productivity	0.177	0.142	0.149	0.036	0.184	0.199	0.610	1	0.920	0.149	0.192	0.227	0.702	0.624	0.716
Man productivity	0.360	0.240	0.280	0.080	0.080	0.080	0.640	1	1	0.320	0.320	0.400	0.480	0.440	0.520
Raw material stocks	0.548	0.545	0.513	0.994	0.991	0.979	0.202	0.533	0	0.921	0.970	0.950	0.872	0.864	0.873
Work in progress	0	0.163	0.339	0.943	0.950	0.899	0.997	0.980	0.988	0.916	0.935	0.914	0.794	0.785	0.839
Finished product stock	0.162	0.198	0.177	0.783	0.809	0.664	0	0.006	0.160	0.389	0.486	0.405	0.363	0.321	0.246
Absenteeism	0.126	0.094	0.186	0.140	0.091	0.233	0.147	0.016	0.215	0.176	0	0.302	0.170	0.129	0.177
Worked hours	0.927	0.959	0.939	0.939	0.954	0.954	0.948	0.860	0.961	0.937	0.944	0.956	0.938	1	0.936
Input															
Number of employees	0.939	0.979	1	0.221	0.236	0.289	0.099	0.109	0.130	0.077	0.070	0.085	0.172	0.204	0.224
Personnel cost	0.838	0.900	1	0.192	0.209	0.260	0.088	0.096	0.113	0.069	0.070	0.081	0.148	0.177	0.210
Investments	0.641	0.412	0.612	0.313	0.129	0.171	0.071	0.103	0.173	0.026	0.063	0.184	0.225	0.243	0.212
Overtime	1	0.863	0.989	0.206	0.197	0.235	0.142	0.112	0.163	0.084	0.084	0.108	0.146	0.175	0.198
Number of staff/personnel	0.932	1	0.994	0.057	0.057	0.063	0.046	0.051	0.051	0.023	0.023	0.023	0.023	0.017	0.017

Table 2. The final ranking obtained by conventional DEA (model (2)).

Plant	A95	A96	A97	B95	B96	B97	C95	C96	C97	D95	D96	D97	E95	E96	E97
Rank	0.713	0.714	0.670	0.815	0.853	0.694	1	1	1	1	1	1	1	1	1

(3) The stepwise approach may be adopted (Norman and Stoker 1991).

Nevertheless, standard DEA results highlight two relatively inefficient productive units (A and B). For the first unit (i.e. unit A) inefficiency may be related to the type of production carried out (the low productivity and the presence of a large amount of personnel are justified by the reworking cycles required). The second productive unit (i.e. unit B) is the largest one in terms of produced quantity (up to seven times the second largest one) and, consequently, the 17 performance factor analysis had to neglect some parameters, such as the net profit and the production added value, because of industrial reserve. A further consideration refers to plant A, which is the legal and administrative unit of the company with a large staff (more than half of the total personnel). This fact implies that about 15% of the employees are involved in managing and directional activities for the whole group of the company plants. As a consequence, in the remainder of the study, the efficiency evaluation will be carried out neglecting the staff consistency, thus obtaining the results shown in table 3 and adopted for further comparisons.

It is useful to point out that the productive units achieving unitary efficiency are the same as those of the previous analysis.

6. The reduction of factors

The discriminatory power of the DEA can be increased by reducing the number of factors considered in the efficiency ratio, taking care to avoid distortion in the outcome of the results. A possible method is to reduce the number of variables, according to their correlation factor (Kim and Hendry 1998, Thanassoulis *et al*. 1987). A high positive correlation between two factors means that each one is well represented by the other one, i.e. both the factors are so closely linked to each other that they offer the same information and, consequently, one of the two can be neglected. Thus, it is necessary to calculate the pairwise correlation between the output or the input factors, deleting those inputs and/or outputs which are strongly correlated. Table 4 represents the higher correlation coefficients.

Table 4 clearly shows how the produced quantity is strongly linked to the scrapped quantity, the idle time and the work-in-progress, thus encompassing the information offered by these parameters and justifying their suppression (e.g. Kim and Hendry 1998); i.e. the exclusion of five factors is permitted (*outputs*: scrapped quantity, idle time, work-in-process; *inputs*: average cost per employee, overtime). Results are offered in Table 5.

Evidently, the reduction of factors considered in the model must represent a correct compromise between the increase of DEA discrimination and the loss of information. For our scope, the DEA discriminatory power has been sufficiently increased, thus avoiding a further reduction of factors. Seven cases are still found to be at the maximum of relative efficiency, but plant E is now revealed to be inefficient in 1996 and 1997.

The reduction obtained is still limited, as both literature and experience suggest that the best results are achieved when the DMU number doubles the number of factors. However, attention is to be paid when suppressing the parameters only on the base of the correlation index datum. In fact, this information may not be meaningful and it may lead to an efficiency concept significantly different from the starting one. Therefore, results obtained can be taken into consideration, but they must be carefully estimated. For example, according to table 4 indications, two further parameters were eliminated (i.e. actual worker productivity and investments) and the results obtained radically contrasted with the previous ones.

7. The cross-efficiency approach

So as to improve the DEA discriminatory power, an alternative approach is represented by the cross-efficiency (Doyle and Green 1994). Once the DEA model for a particular plant has been chosen, the best set of weights calculated can be used to weigh the inputs and outputs of every other productive unit. Hence, a square matrix of cross-efficiencies may be arranged, where the ith row refers to the efficiency of each productive unit, calculated according to the weights set for the ith productive unit, and the kth column refers to the efficiency of the kth productive unit calculated according to the weights set for each unit.

The results of the cross-efficiency matrix may be summed up by calculating, for each row i, the average of its values, neglecting the value pertaining to the main

Table 3. The final ranking obtained by conventional DEA without number of staff/personnel.

Plant	A95	A96	A97	B95	B96	B97	C95	C96	C97	D95	D96	D97	E95	E96	E97
Rank	0.817	0.713	0.760	0.722	0.754	0.581	1	1	1	1	1	1	1	1	1

Table 4. Correlation index values.

Factors			Correlation index value
Produced quantity	→	Scrapped quantity	0.995
Produced quantity	→	Idle time	0.963
Produced quantity	→	Work-in-process	0.965
Scrapped quantity	→	Idle time	0.970
Scrapped quantity	→	Work-in-process	0.942
Idle time	→	Work-in-process	0.928
Number of employees	→	Avg. cost per employee	0.990
Number of employees	→	Overtime	0.992
Avg. cost per employee	→	Overtime	0.985
Actual plant productivity	→	Actual worker productivity	0.895
Number of employees	→	Investments	0.909

Table 5. Final ranking with DEA after the reduction of factors.

Plant	A95	A96	A97	B95	B96	B97	C95	C96	C97	D95	D96	D97	E95	E96	E97
Rank	0.817	0.708	0.760	0.557	0.588	0.415	1	1	1	1	1	1	1	0.924	0.974

diagonal (average efficiency of units other than i evaluated according to the set of weights most favourable to the ith unit). The diagonal values E_{jj} correspond to the traditional simple efficiency measurements for each plant (obviously $E_{jj} \geq E_{ij}\,\forall i$). A similar average may be calculated for each column k, thus obtaining the average efficiency of the kth unit according to the set of values most favourable to the other units, i.e. the cross-efficiency of the kth plant e_k. The procedure allows the identification of those units whose relevant efficiency is the consequence of a choice of significantly unbalanced weights. To this end, the 'Maverick index' M_j of the jth productive unit may be useful, as it suggests the calculation of the percentage deviation obtained when moving from the traditional simple efficiency E_{jj} to the corresponding cross-efficiency e_j, i.e.:

$$M_j = \frac{E_{jj} - e_j}{e_j} \cdot 100$$

A productive unit associated with a high value of the Maverick index, when evaluated as efficient by the standard DEA approach, may be overestimated because of poor discrimination. However, cross-efficiency limits are evident when the choice of a set of weights is considered: several sets may lead to the maximization of the efficiency and the choice of one of these sets is a random process, sometimes linked to factors such as the order of data presentation or the steps of the algorithm adopted. Doyle and Green (1994) suggest introducing, in addition to the efficiency, a further objective function to be maximized or minimized. Two distinct approaches are available: the 'aggressive' and the 'benevolent' one. An 'aggressive' productive unit tends, at first, to maximize its efficiency and then to penalize the other units' efficiency, minimizing them. On the contrary, a 'benevolent' unit tends to approach the other units' efficiency, maximizing them. This procedure requires two distinct steps:

(1) Applying a standard DEA technique to maximize the single unit efficiency (this is the one and only target at this step).
(2) Solving an LP model with a new objective function that, once made conveniently linear by a *proxy*, represents the average of the cross-efficiencies obtained for the other units when ranked by applying their own best weights. The target obtained in step (1) is maintained by adding a

Table 6. Cross-efficiency results.

Plant	'Aggressive' method		'Benevolent' method		Average	
	Cross-efficiency	Maverick index	Cross-efficiency	Maverick index	Cross-efficiency	Maverick index
A95	0.232	2.524	0.575	0.422	0.403	1.026
A96	0.232	2.072	0.549	0.301	0.390	0.828
A97	0.226	2.367	0.543	0.402	0.384	0.979
B95	0.265	1.728	0.250	1.890	0.258	1.807
B96	0.317	1.380	0.294	1.567	0.305	1.470
B97	0.276	1.106	0.266	1.192	0.271	1.148
C95	0.394	1.537	0.471	1.123	0.433	1.311
C96	0.496	1.015	0.582	0.720	0.539	0.856
C97	0.534	0.873	0.691	0.447	0.613	0.633
D95	0.868	0.153	1	0	0.934	0.071
D96	0.686	0.457	0.893	0.119	0.790	0.267
D97	0.652	0.534	0.788	0.270	0.720	0.389
E95	0.602	0.661	0.879	0.137	0.741	0.350
E96	0.496	1.015	0.780	0.282	0.638	0.567
E97	0.500	0.998	0.806	0.241	0.653	0.531

further limit, namely, requiring that the efficiency of the unit considered be equal to the one obtained in such a step.

For further details of cross-efficiency, the reader may refer to Doyle and Green (1994).

Table 6 offers the results obtained by the two methods described, together with their averages. Plant D95 turns out to be the most efficient one, also presenting the lowest Maverick index: it remains the most efficient, but its performance decreases both in 1996 and 1997. Unit E has a high efficiency level, too (in 1995 it is superior to D97) and its performance is more constant over time. In the two last years considered, plant D saw a personnel reduction and a high plant utilization thanks to the investments made. It is also affected by single product manufacturing (high volumes and poor technology) with limited added value. Investments in plant E aimed to increase productivity and equipment utilization, acting on a simple product-cycle with few operations. Unit C performance collapses, showing how its performance characteristics were unbalanced (its high efficiency was a false indication, being affected by a chronic incapacity to interact with the other units). Finally, plants A and B confirm their basic inefficiency.

8. The stepwise approach

This approach (Norman and Stoker 1991) is based on the assumption that there must be a number of factors that are seemingly related to the concept of efficiency that the model aims to evaluate (Kim and Hendry 1998). The starting point is the definition of a concept of efficiency as the ratio between one single output and one single input. The two-factor DEA model is implemented and the ranking results are correlated with the remaining performance criteria. The necessary condition is that there exist a certain number of criteria correlated with the initial definition of efficiency: the factor showing the strongest link is suitable for a complete explanation of the efficiency defined. The procedure is iterated until no more factors show a strong correlation with the model.

The advantage offered by this approach consists in its guaranteeing the presence of only those factors which are able to explain the initial concept of efficiency (i.e. the ratio between two initial variables), thus excluding the over-abundant or distorting factors. The initial identification of a two-factor significant efficiency is not an immediate process: before implementing the model, it is necessary to carefully analyse the situation and justify the choices made. To overcome this problem, the analysis started with the identification of three possible pairs of input and output factors, i.e.:

(1) Produced Quantity/Investments: for the same amount of material produced, the lower the investment, the higher the efficiency.
(2) Produced Quantity/Number of Employees: a larger quantity produced by a lower number of the employees implies a better efficiency.
(3) Non-operating Time/Personnel Cost: increasing the working time of the plant allows the reduction of employees' cost, thus increasing the plant performance.

According to DEA results, the first ratio offered a performance which is not strictly linked to the other parameters considered: the highest correlation index is limited to 0.31 and this model was consequently abandoned. The second model led to the calculation of a significant performance value for each plant: paradoxically, the relevant correlation with several other parameters does not allow the augmenting of the limited DEA discrimination (each time an attribute is added, a further one shows an important link with the starting concept). This event was recorded for 10 successive implementations of the model and the resulting selectivity was so limited as to give nine plants a performance equal to one.

In order to improve the effectiveness of the method, the iterative process was suspended when, after adding a factor, the average of the plant efficiencies increases by less than 5%. Consequently, the process stopped after three DEA implementations, i.e. after adding to the initial ratio only two new parameters: the utilization index and the actual worker productivity. Results are shown in table 7 where only three productive units score a unitary performance.

However, the four factors utilized may refer to a particular aspect of efficiency, which may not be relevant for all the plants (some of them may dedicate resources to other performance criteria, thus obtaining an overall positive result). The technique roughly confirms previous results: plant B presents a weak performance, plant A gains a performance close to the maximum value (conventional DEA showed how this plant assigns its highest weights to the produced quantity and to the number of employees, while plant B focused on finished product stocks, absenteeism and overtime). The third concept of efficiency was significant, too: it was possible to adopt the conventional stopping procedure of the iteration process (Kim and Hendry 1998), i.e. when the correlation values between efficiency and the parameters not included in the ratio is less than a set value (present case: 0.6).

Table 7. DEA final ranking after stepwise approaches starting from two different efficiencies.

Plant	$\frac{\text{[Produced qty]}}{\text{[No. employees]}}$	$\frac{\text{[Idle time]}}{\text{[Personnel cost]}}$
A95	0.759	0.818
A96	0.625	0.708
A97	0.697	0.761
B95	0.575	0.366
B96	0.543	0.378
B97	0.357	0.303
C95	0.836	0.948
C96	0.799	0.880
C97	0.888	0.904
D95	1	1
D96	1	1
D97	0.988	0.985
E95	1	1
E96	0.907	0.925
E97	0.922	0.975

Thus, the difference with the second concept is that no stopping rule other than the correlation coefficient is required to obtain an adequate selectivity. Four factors were added to the initial couple: investment, number of employees, produced quantity and utilization index. DEA discrimination is rather sensitive (table 7) and, also in this case, three plants show a unitary efficiency (D95, D96 and E95).

9. Cluster analysis

The possibility of investigating the different DEA results is offered by *cluster analysis* (e.g. Proth and Hillion 1990): it also allows productive units to be grouped into homogeneous families and to analyse the behaviour of each single plant over time. *Cluster analysis* is a technique used to identify and group sets of data: objects pertaining to groups may be both 'cases' and 'variables' and they are grouped into homogeneous categories or families; homogeneity definition depends on the criteria chosen to measure the distance between the entities themselves. Two well-known cluster techniques are hereafter adopted: *Hierarchical clustering* and *K-means clustering*.

The entities observed are the plant observations: each unit shows a set of results which defines the efficiency value obtained by DEA implementation (for each productive unit, these results could be different: tricks introduced should be able to modify the performance concept associated with standard DEA). Each plant observation, i.e. each entity, is described by the following parameters:

(1) Standard DEA.
(2) Cross-efficiency averages, obtained by 'aggressive' and 'benevolent' approaches.
(3) Maverick indices referring to the average of the two approaches (cluster analysis requires data standardization: the Maverick index may be greater than one and it must be normalized to avoid its excessive weight in the distance calculation; however, the lower the index, the higher the performance and, consequently, normalization is carried out on the index reciprocal).
(4) The stepwise approach, starting from the ratio between produced quantity and number of employees.
(5) The stepwise approach starting from the ratio between idle time and personnel cost.
(6) DEA relative to the reduction of four factors after the correlation analysis.

The generic observation is an ordered vector of six elements obtained from each productive unit, e.g. according to the previous data sequence, plant C95 observation is:

$$C95 = [1, 1, 0.8357, 0.9475, 0.4327, 0.2742]$$

9.1. *Hierarchical clustering*

The hierarchical cluster obtained by adopting Euclidean distances leads to the dendogram represented in figure 1: it shows how it is possible to identify each cluster composition by successive steps (iterations). The first column gives the productive units, as involved by the software iterations, which are carried out by considering the closest couple of clusters. The horizontal axis offers the aggregation levels obtained at each iteration. The highest level (i.e. 25) is linked to the situation of a unique cluster encompassing all of the DMUs.

The dendogram of figure 1 shows how an aggregation level equal to eight singles out three separate situations of different efficiency. Moreover, figure 1 results highlight the plant behaviour over time: movement from one group to another suggests a certain degree of performance diversity (even though not accentuated). Such diversity may be positive (the efficiency is slightly higher than the cluster average) or negative. For successive analyses, the subdivision adopted is based on three clusters. In this case, an acceptable variability of the values within each cluster was recorded.

The average of the efficiency values of the three clusters indicates that one cluster offers high performances, a second one is associated with intermediate performances and the last one, in each phase, to relatively poor performances. Data shown suggest the grouping of D, E and C97; only at a low aggregation level (six clusters) D95 parts to create a unitary cluster. Referring to intermediate aggregation, plant A is grouped together with C95 and C96: this aggregation is not very robust, as at the level immediately below plant C emerges, thanks to a superior overall performance.

Plant B has always been the least efficient plant and the hierarchical analysis leads to a specific cluster including, at each level, all of the corresponding units: a six-group configuration leads to B97 separation because of an efficiency value lower than the two preceding years.

Generally, observations of a single plant over various years appear in the same cluster, exceptions being C95 and C96 (cluster 1, i.e. intermediate performance) while C97 belongs to cluster 3 (highest efficiency units). The shift is related to a produced quantity increase of about 40%, thanks to investment focused on better utilization of equipment and greater number of worked hours. The positive effects of these and further investments were detected, as expected, in the successive years.

9.2. *K-means clustering*

The hierarchical analysis suggested the grouping into three clusters: on this basis, the K-mean analysis is carried out, calculating the distances between the group centres (i.e. barycentres). The distance of each plant

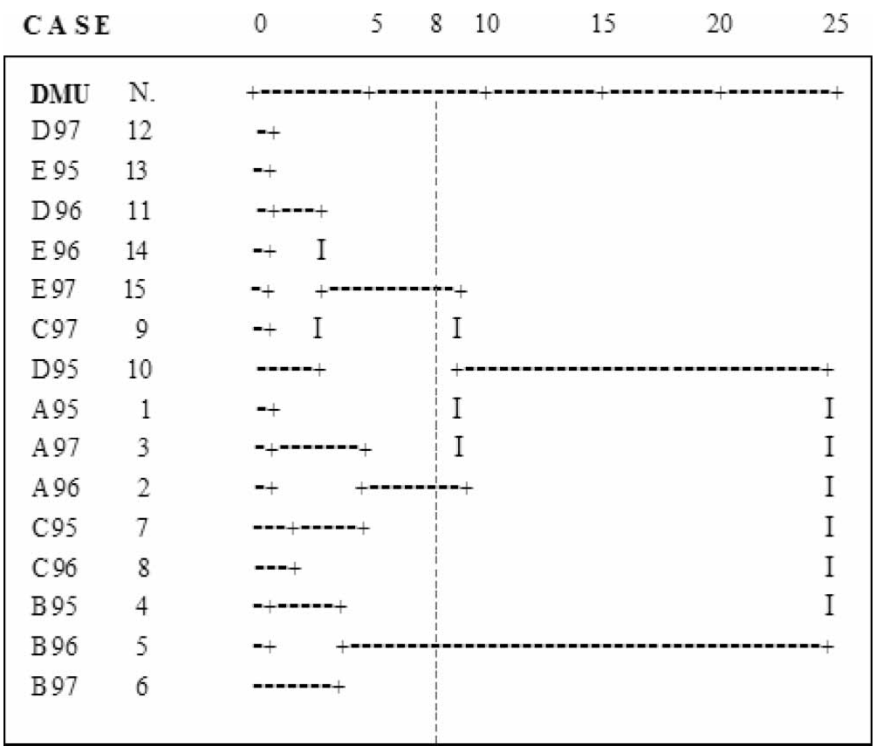

Figure 1. Dendogram of the hierarchical analysis referring to a maximum number of six clusters.

from the barycentre of its own cluster is shown in table 8 (for the distances evaluation see, for example, Proth and Hillion 1990): the higher the distance, the higher the possibility that the observation will leave the group at the aggregation level immediately below. For example, C95 and C96 appear in a position sufficiently far from their cluster centre, especially when compared to the other units of the cluster itself (the previous hierarchical analysis showed how the two units above, at the aggregation level immediately below, form a cluster independently from plant A). The same can be said for D95 (third cluster) and B97 (second cluster). However, in the case of D95, C95 and C96 the greater distance indicates a slightly higher efficiency with respect to the other plants; the opposite is true for B97 and A96.

The K-means analysis also allows the calculation of the cluster barycentre: in the case under examination, this point pertains to the six-dimension space R^6 and its coordinates are a vector whose components represent the average of the efficiency values obtained by the plants pertaining to the cluster (table 9): naturally, these components are highest for the third cluster.

Table 10 shows the distance between the barycentres: the closest clusters are the first and the third ones, whilst the second is more distant. Once again, this fact highlights the inefficiency of plant B.

In conclusion, K-mean cluster analysis allowed the identification of three separate clusters, characterized by different efficiency levels, thus confirming via mathematical tools the observations made by the different DEA applications. It also made it possible to focus on the different behaviour of the plants over the three-year period analysis.

10. Economical analysis

The previous analyses may offer useful indications to the company management. The most relevant aspects concern (i) the identification of the input/output variables that must be changed to allow inefficient plants to reach a unitary performance and (ii) the required range of these changes. In particular, it is important to quantify the minimum modification of the input factor leading to the maximum relative performance. This kind of analysis allows the identification of parameters that are lacking with respect to the alternative ones and it may be solved by the DEA dual model (e.g. Braglia and Petroni 1999).

In the present case, the analysis of duality was carried out with reference to the stepwise approach, which explained efficiency by five factors (two outputs and three inputs) and led to the identification of three plants with a unitary efficiency (D95, D96 and E95). This approach emerged as the best compromise between discriminatory power, significance and number of performance parameters considered.

Table 11 shows the percentage variation that the factors in question should undergo in order for the plant to be considered efficient, reaching a unitary relative efficiency. Actually, there are infinite combinations of parameters leading to the result, as both a further input reduction or an increased output may strengthen the performance.

In table 11, the simple numeric value has no significant interest: the dual problem offers good indications as to which parameters are worthy of intervention, rather than the entity of their modification. This is the case of plant A95: to reach a unitary efficiency, this plant should manufacture the same quantity of finished products while

Table 8. Distance of each DMU from the centre of its own cluster.

Case number	Plant	Cluster	Distance
1	A95	1	0.075
2	A96	1	0.298
3	A97	1	0.178
4	B95	2	0.211
5	B96	2	0.116
6	B97	2	0.276
7	C95	1	0.307
8	C96	1	0.289
9	C97	3	0.187
10	D95	3	0.281
11	D96	3	0.109
12	D97	3	0.036
13	E95	3	0.059
14	E96	3	0.160
15	E97	3	0.110

Table 9. Cluster centre components.

	Cluster		
	1	2	3
Reduced DEA	0.85734	0.520333	0.985571
Total DEA	0.85828	0.686329	1
Cross-efficiency	0.429881	0.277929	0.726793
Maverick index	0.446398	0.183603	0.777988
Stepwise b	0.74292	0.4915	0.957829
Stepwise c	0.85296	0.3678	0.978486

Table 10. Distances between cluster centres.

Cluster	1	2	3
1	–	0.730673	0.54459
2	0.730673	–	1.208308
3	0.54459	1.208308	–

Table 11. Percentage variation of factors considered obtained by dual analysis.

		Output increase		Input decrease		
Plants	Efficiency	Idle time	Produced quantity	Personnel cost	Investments	Number of employees
A95	0.817	96.20	0	19.36	18.25	18.25
A96	0.708	97.32	0	31.07	29.18	29.18
A97	0.760	97.34	0	32.74	23.92	23.92
B95	0.366	0	71.56	63.40	91.65	64.71
B96	0.377	0	73.74	62.22	77.16	62.74
B97	0.302	0	47.14	69.71	82.74	69.84
C95	0.947	0	56.24	5.25	57.82	5.64
C96	0.880	0	11.02	11.97	70.46	13.58
C97	0.904	0	0	9.56	56.12	10.74
D95	1					
D96	1					
D97	0.984	0	0	1.53	54.43	1.53
E95	1					
E96	0.924	48.47	0	7.82	7.55	7.55
E97	0.974	67.88	0	8.95	2.55	2.55

cutting the investment by 19%, reducing personnel by 19% and reducing the idle time by 96%. This situation is clearly associated with excessive variations of the parameters, this also being a consequence of the five-factor approach. In reality, there are other factors on which it is possible to act in order to reach the unitary relative efficiency, without adopting such a dramatic intervention. Of the five parameters considered, the dual analysis highlights the most critical ones and, consequently, those suitable for intervention. According to these concepts, it is possible to state that D95, D96 and E95 do not require any factor modification. In the three years considered, plant A's most critical parameter is the idle time, which is also the consequence of the company strategy to privilege the flexibility of this plant, so as to promptly reply to every market requirement, and consequently incurring notable set-up times. The same is true for E96 and E97, together with the need for a limited reduction of the inputs (e.g. reduction of personnel cost of 9%). Plant B showed a low efficiency which determined a significant decrease in inputs. Over the three years considered, the idle time is a sufficiently utilized factor, while the low quantity produced requires an increase (this performance is strictly linked to the kind of production, i.e. stainless steel welded pipes).

11. Conclusions and remarks

A relative evaluation of the performances of different plants of the same company was proposed, according to Data Envelopment Analysis (DEA). Operative data from five plants were analysed over three years, adopting several variants of the conventional DEA technique: factor reduction, cross-efficiency and stepwise approach. A cluster analysis allowed the grouping of data, thus identifying three separate groups characterized by different efficiency levels and offering a mathematical validation of the results obtained by the different DEA applications. This approach also allowed the critical analysis of each plant performance over the three-year period in question. The dual analysis of DEA offered a series of economical considerations on the results obtained.

It can be stated that DEA application to a wide set of data may be extremely positive in industrial cases. In fact, both efficiencies and inefficiencies detected have found a positive confirmation in the typologies of the productive systems and in the strategic choices made by the management. The analyses could offer further results of great interest to industry if other parameters, e.g. product added value and net profit, are included in the analysis. The economic analysis carried out clearly addressed the parameters worthy of attention in favouring plant efficiency. In this case, too, a confirmation was detected with reference to the industrial case under consideration.

Finally, we would like to discuss a problem that could be considered as a limitation to this approach. The question concerns the absolute performance level of the best plants in the company. A reader could observe that the plant characterized by a unitary efficiency (obtained from the relative ranking of the company's plant) could not be, in the same way, particularly efficient in absolute terms (i.e. if compared to plants of other companies). Therefore, it could be asserted that the DEA's results are useful only for well-operated companies where the expected performance level of the best plant is recognized as being *a priori* very good. In the same way, for a poorly-operated company, generally characterized by inefficient plants, the DEA analysis could be useless. In such a situation, every plant needs to be improved, i.e. also the plants showing efficiencies equal to one. To overcome this limitation it is possible to introduce a fictitious series of references characterized by excellent values in terms of inputs and outputs considered. For example, it is possible to create this fictitious plant assigning each input and output variable the best values obtainable from the set of plants under analysis (e.g. characterized by the highest volume produced, the lowest scrapped quantity, etc.). Alternatively, it is possible to create *ex-novo* a fictitious plant where the inputs and outputs represent the desired values of the management. In this way, the plant of reference turns out to be the only one characterized by a unitary efficiency while all the other plants show various inefficiencies that must be solved. In the industrial case reported here, this approach was not required *in virtue* of the recognized high operative levels distinguishing the best plants of the company.

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