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ORIGINAL ARTICLE

Cost drivers-based method for machining and assembly cost estimations in mould manufacturing

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Abstract Dies and moulds represent an essential element in manufacturing process and significantly influence the fabrication time and cost of the products. Moreover, the market continuously asks the die manufacturers for products that have better characteristics in terms of finishing, complexity or flexibility within a reduction of the time to market and cost, so as to follow the rapid changes in the product design. Therefore, in order to give to the customer the best cost-performance solution, companies require accurate and reliable tools for die manufacturing cost estimation both for commercial purposes and for comparisons amongst different design solutions. In this context, the paper proposes a method for manufacturing cost estimation based on the definition of cost drivers. The method was implemented using a database coming from a company specialized in the production of dies for sheet forming and rubber injection and it allowed to estimate a cost estimation relationship (CER) function that is able to correlate the cost drivers with the manufacturing cost of machining and assembly phases. In particular, the method allowed to overcome the limitations related to the available data as the company's own storage criterion, unbalancing and high and non-uniform scattering that do not allow use of the variance analysis technique.

Keywords Cost model · Manufacturing · Die · Assembly · Machining

1 Introduction

Technological innovation, market internationalization and customer requests have significantly reduced the product life making them rapidly obsolete. Furthermore, the dynamic competition scenario has led the companies to produce higher quality products with lower lead time and costs.

Near net shape processes as injection moulding or casting allow to respond to the market requests since they reduce the number of steps in the manufacturing process, although they involve dies and moulds whose cost can represent a high percentage of the total product. In fact, assuming a die life of 250,000 injections, the die can cover up to the 45 % of the cost for an automotive moulded part [1]. Therefore, the die cost estimation assumes a significant role in a competitive market. Moreover, according to Freiman's curve (Fig. 1), a company needs tools for a realistic and reliable estimation of the product costs since both the under- and overestimations of the product costs lead to negative consequences [2]. In particular, even if the cost underestimation increases the probability to sell a product, it leads to financial losses. Otherwise, its overestimation causes an overallocation of resources and a loss in the company competitiveness. In order to correct the errors induced by bad estimations, the company can make changes to the product and its manufacturing process, but this leads to a more rapid allocation of resources and the freedom of action decreases as their development proceeds (Fig. 2) [3]. It is therefore fundamental for companies to have reliable tools able to estimate the costs starting from the first phases of the product development.

Companies got four different methods to develop cost estimation models: intuitive, analogical, analytic and parametric (Table 1).

The intuitive methods are based on personal experience; they are therefore subjected to a high variability according to knowledge, skills and competence of the evaluator, and they are difficult to be formalized in exploitable rules. On the other hand, their use has less time and is cost consuming. Therefore, they are adopted in small production companies where the product development phases are not strictly formalized [5].

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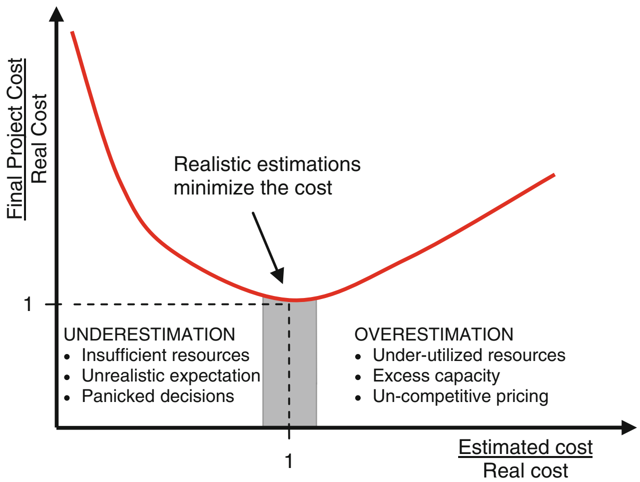


Fig. 1 Freiman's curve [4]

The analogical methods compare a new product with the existing ones using technical similarities and dissimilarities. They require skilled people to associate the dissimilarities to differences in the cost; therefore, they are partially subjected to the limits of intuitive ones. Typically, they are adopted in the first phases of the product life cycle (i.e. feasibility, definition and development) and in after-sales services [5]. Some examples are the case-based reasoning (CBR) [6, 7] or the group technology (GT) [7] methods. CBR methods are fast, they can use both quantitative and qualitative data and allow correcting of the previous estimation errors, but they require a detailed and organized database. In addition, the definition of comparison indexes and their implementation are complex, therefore they are not suitable for SMEs. GT methods are similar to CBR, but they group the products in homogeneous families having the same morphological or technological characteristics. Therefore, the database can be organized according to the product's existing classification.

The analytic methods are bottom-up approaches that identify each elementary part or task of the manufacturing process, then they estimate the costs of each task and sum them. They are mainly used from the definition to after-sales phases [5].

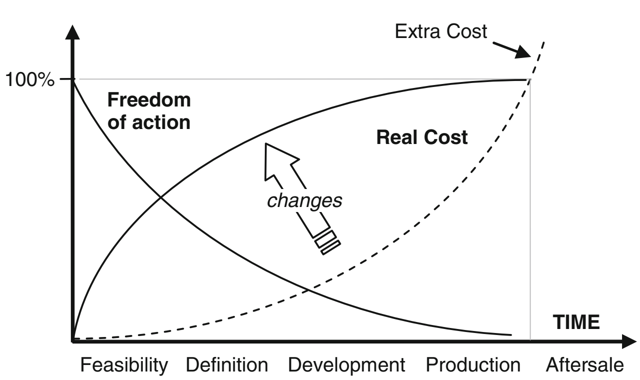


Fig. 2 Freedom of action and costs associated with changes during the product life cycle [3]

Activity-based costing (ABC) models are examples of analytical method application and they consider the resources required in each activity (i.e. material, time, energy, customer service). In general, ABCs result to be the most precise models for cost estimations, especially when indirect costs are predominant, since they are based on causal correlations between products and costs and they can be applied to realities having a wide variety of products or services. On the contrary, errors in direct cost estimations can make ABCs very imprecise, making them not suitable in realities where the final cost is mostly composed by direct costs. Moreover, they require lots of detailed information for the estimation of the activity costs. They spread in the 1980s in many manufacturing sectors such as automotive, aerospace, naval and telecommunications [8–10].

Finally, the parametric methods use cost drivers (i.e. design technical data as volume, weight, material or finishing) that influence the final cost and correlate them using analytical functions without knowing the specific details of the products. These functions are known as cost estimation relationship (CER) and are based on statistical approaches and interpolations on normalized data. Since these methods are based on aggregated data, they are adopted in product feasibility and definition phases, wherein the product details have not been defined [5]. Parametric models are characterized by ease of use, do not require complex software for their implementation and highlight the impacts of the cost drivers on the final cost. Otherwise, the data normalization can be time consuming; moreover, the use of aggregate data requires a good database and it can show false dependences.

Methods application mostly depends on the availability of product details, cost data and the time needed for their development [5], therefore the few models which are present in literature for die and moulds cost estimation are obtained by joining the different methods. Semi-analytic models were developed to estimate the CNC cutting costs [2] or to adapt a CBR-based method [11], while models obtained from parametric and analytic methods were used to estimate the cost of injection moulds in [12, 13]. In [14] the parametric and analytic methods were used together to develop a model that can be exploited to manufacture moulds for different applications. In general, they require both generic information (main dimensions, volume of material to remove, surface finishing) and details about the manufacturing process (cutting parameters, accessories to be assembled, production time and time-dependant costs). In particular, the latter make these models not applicable in the preliminary phases of the products and represent a limit for their use in quotations.

For these reasons, the paper presents a parametric model based on multivariate regression and able to correlate aggregate cost data with mould general characteristics. In particular, the method will be implemented in machining and assembly costs estimations to identify the most significant cost drivers. Then, different CER functions will be estimated and compared in

Table 1 Summary of the cost estimation methods

Method	Pros	Cons	Suitable phases
Intuitive	Rapid	Low precision Skilled evaluators Difficult to be exploited	All product phases
Analogical	Estimations with less time and cost	Difficult to define the concept of similitude	Feasibility
	Allows to correct errors thanks to continuous database updating (CBR)	Requires a reliable database	Definition
		Limits in innovative products because of low similarity products	Development After sale
Analytic	Accurate estimation	High implementation cost for data collection and organization which can overcome the pros	Definition Development
	Allows to allocate indirect costs	Not suitable when direct costs are preponderant	Production Utilization
Parametric	Rapid and easy to use Low cost Quantitative and qualitative parameters Highlights the relation between parameters and cost	Risk of uncertain results Reliable and solid database	Feasibility Definition

order to identify the best compromise between accuracy and function complexity. It will be shown how the proposed model can be implemented using a database containing both numerical and non-numerical data that cannot be elaborated using variance analysis techniques. Moreover, it will result in adaptability to the company's criteria used for die characteristics classification. Finally, the comparison between predicted and historical data will demonstrate the reliability of the proposed model and its capability to overcome the high scattering of the initial data.

2 Cost model

The die manufacturing process is composed by many operations such as design, machining, non-conventional machining, surface finishing, heat treatment, assembly and testing. Each operation is characterized by its own cost and specific cost drivers. The model here described is proposed both to identify the significant cost drivers of each operation and to estimate a CER function for manufacturing cost estimation.

In general, company historical data are characterized by a non-homogeneous variance within the groups and they can be non-numerical ones. Therefore, they can neither be analyzed using variance techniques nor being directly used in numerical functions like CER. Therefore, to overcome these limits, the present model proposes a standard procedure for representing non-numerical data using dummy variables. Moreover, it evaluates the significance of the cost drivers in terms of their contribution to the accuracy of the CER function. In particular, this procedure is adaptable to the company criterion for non-numerical data classification.

The following section will describe the model and show its implementation using a database kindly provided by a company specialized in designing and manufacturing of dies and moulds for sheet drawing, cold bulk forming and rubber injection moulding.

Table 2 Database for assembly costs in sheet bending dies manufacturing (sheet bending dies/assembly operation)

Information	Data	Type	Values
Dimensions of the die (plant)	Rectangular		
	Length (L)	Range	$L = L_1 \div L_2$
	Width (W)	Range	$W = W_1 \div W_2$
	Circular		
	Diameter (D)	Max value	$D \leq D_{max}$
Number of stages	N	Numerical	1–2
Required precision	P	Text	Low–medium–high
Manufacturing difficulty	MD	Text	Low–medium–high
Sheet loading system	LS	Text	Automatic–manual–coil
Database entries	27 dies		

Table 3 Database for machining costs in injection moulding dies manufacturing (rubber injection/machining operation)

Information	Data	Type	Values
Dimensions of the die (plant)	Rectangular		
	Length (L)	Range	$L = L_1 \div L_2$
	Width (W)	Range	$W = W_1 \div W_2$
	Circular		
	Diameter (D)	Max value	$D \leq D_{\max}$
Number of cavities	N	Numerical	1–2–3–4–24
Required precision	P	Textual	Low–medium–high
Manufacturing difficulty	MD	Textual	Low–medium–high
Die typology	T	Textual	15 Different classifications
Database entries	69 dies		

2.1 Database description

The database used in the present study refers to dies used in sheet and rubber forming. It contains information about their applications, geometrical and morphological characteristics, complexity, manufacturing processes and costs of the most significant manufacturing operations. According to the database, the cost of the dies for sheet bending and rubber injection moulding applications is mainly due to the cutting and the machining operations, respectively. Tables 2 and 3 report the available information on the products. In particular, die dimensions (L, W, D) are stored as ranges, while other details are classified in different levels. Moreover, sheet forming dies differ on the loading system (LS), which can require additional features for the centring sheet (manual) or the feeding system (coil), and they can be divided in stages for the sheet deformation (N). Injection moulding dies can hold more cavities of the same part (N), and they are classified by the company using a high number of arbitrary typologies (T) according to the presence of additional features or treatments as centring for assembly, slider guides or surface treatments. In general, data are stored in non-uniform ranges, and they are not balanced amongst the levels, they have neither equal variance nor normal distribution. Figure 3 reports the equal variances test results for the assembly dataset where the low p values in Levene's tests show the non-uniform variance amongst the data. Similar results in Bartlett's and F tests are derived from the non-normality of the data.

Finally, data refer to a time lapse which does not require an actualization of the costs (i.e. related to human labour cost or materials price) and will be reported here as normalized values.

2.2 Cost drivers definition

The ranges used to store the die dimensions data are not unique but in general overlap each other; therefore, a reference cost driver S was estimated according to (1). It aims to represent the surface of the die on the parting surface. Average values of L, W and D within the ranges were estimated according to (2) where the single dimension is generally called

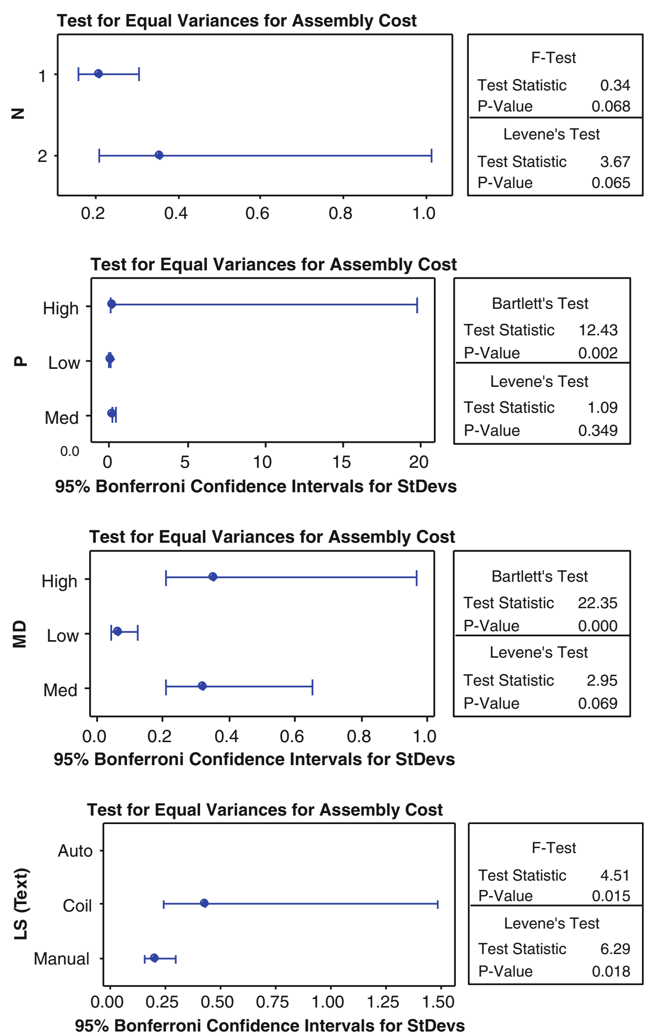


Fig. 3 Equal variance tests on available data (assembly–sheet bending)

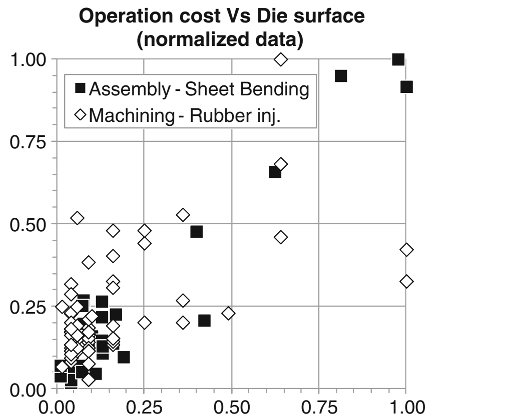


Fig. 4 Correlation between the operation cost and the surface of the die (normalized values)

B. A distinction between the ranges for smaller dies ($B \in [0;B_2]$) and wider dies ($B \in [B_1;B_2]$) was made assuming, respectively, a linear increasing and decreasing frequency of the values amongst the range limits. In fact, in the former case, the B values close to 0 are less frequent, while for the latter, it is more probably an oversized die parting surface due to the dimensional constrains in adapting the die to standard die holder. These assumptions lead to the relationship between the die surface and costs reported in Fig. 4:

$$\begin{cases} S = L \cdot W & \text{rectangular surface} \\ S = \dfrac{\pi}{4} D^2 & \text{circular surface} \end{cases} \tag{1}$$

$$\begin{cases} B = \dfrac{2}{3} B_2 & B \in [0; B_2] \\ B = B_1 + \dfrac{1}{3}(B_2 - B_1) & B \in [B_1; B_2] \end{cases} \quad \text{where} \quad B = L, W, D. \tag{2}$$

In order to use the cost drivers in a CER function, it was necessary to assign a numerical value to the textual cost drivers. Therefore, they were stratified in groups according to their textual value, and the average cost of each group was estimated, normalized and assigned to the dummy variables. In particular, the values 1 and 9 were assigned to the groups having the lowest and highest average costs, respectively, while other values were properly assigned to obtain a linear correlation between the drivers and their average costs. Figure 5 shows the procedure results for the precision cost driver P in assembly and machining operations, and Fig. 6 reports the results obtained with the other drivers.

2.3 CER and cost drivers selection methodology

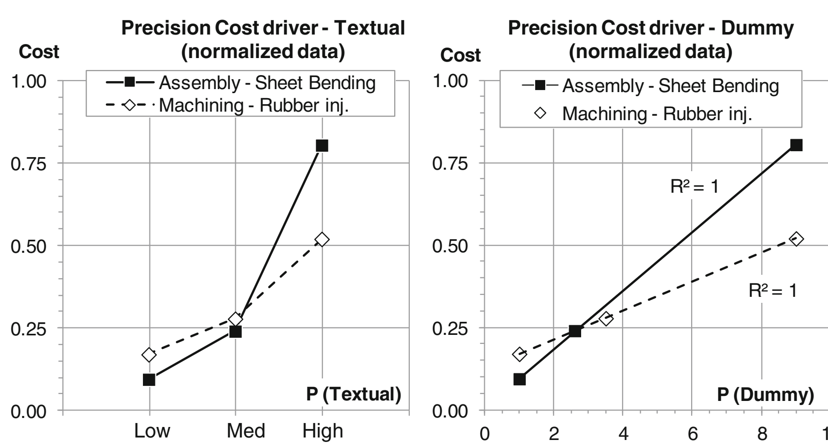
After the introduction of the dummy values, it was possible to express the CER as their function and then evaluate their importance. It was chosen to express CER as a linear combination of the cost drivers x_k, their interactions $x_k x_j$ and quadratic forms x_k^2 as reported in (3) where α_0, α_k, β_{kj} and γ_k are the linear coefficients of the CER function. The linear correlation between CER results and database values (R^2) and the standard deviation of the residuals (σ_e) were used to evaluate the accuracy of the function. The former represents the average accuracy and the latter indicates how its error is distributed.

The non-significant cost drivers were then identified and removed to obtain a good compromise between accuracy and simplicity. Since cost drivers scattering is not uniform (Tables 2 and 3), it is not possible to perform variance analysis; therefore, a numerical approach was performed. In particular, the significance of the cost drivers was evaluated considering their impact on the accuracy (R^2 and σ_e values):

$$\mathrm{CER} = \alpha_0 + \sum_{k=1}^{p} \alpha_k x_k + \sum_{k=1}^{p-1} \sum_{j=k+1}^{p} \beta_{kj} x_k x_j + \sum_{k=1}^{p} \gamma_k x_k^2. \tag{3}$$

Table 4 reports the results of the multivariate interpolations of the data using the cost drivers defined in the previous section. $\mathrm{CER}_{\mathrm{All}}$ refers to the regression obtained using all the cost drivers and the data, $\mathrm{CER}_{\mathrm{Red}}$ is the function obtained reducing the number of the cost drivers, and CER is the final

Fig. 5 Example of dummy variable assignment to cost drivers (required precision P)



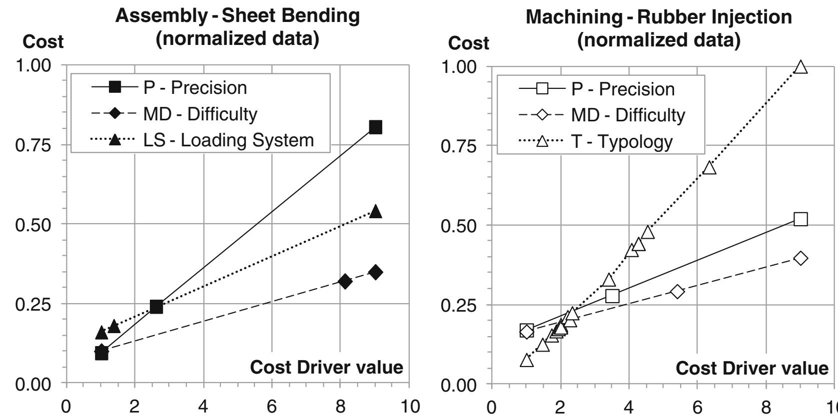


Fig. 6 Results of the dummy values assignation to the cost drivers

function obtained removing the outliers from CER_{Red}. Figures 7 and 8 show and compare the results and the distribution of the residuals.

3 Discussion

The described methodology was applied to a raw set of data that could not be studied through variance analysis. The limits were related to the presence of unbalanced data, not uniform data scattering and storage. In particular, die dimensions were stored in non-uniform ranges, and textual information were used to describe and classify the dies properties and data scattering was not normal or uniform (Fig. 3).

Equations (1) and (2) were introduced to overcome the die dimensions problem in estimating the S value that represents the die parting surface. Figure 4 shows an almost linear correlation between S and the assembly cost that could be explained as a correlation of the die dimensions with the number of parts to assemble or with handling and movement times. With regard to the machining cost in sheet bending dies, it has a no linear correlation and the data are more scattered. Since in the CER function does not show any significant quadratic influence of the S value (Table 4), the non-linear behaviour can be an artefact of the high scattering and unbalancing of data.

With regard to the dummy variables that were introduced to quantify the textual cost drivers, they can have very close values within the same cost driver (Fig. 6). In fact, in assembly cost, LS assumes the values of 1 and 1.1 for the manual and automatic loading systems, respectively. The difference can be only numerical or correlated with the different characteristics of the die (i.e. centring sheet devices), but in both cases it has a low impact on the die cost. Therefore, this suggests choosing between the two solutions according to other cost criteria (i.e. based on purchasing, inventory or resource allocations) aside from the customer's requests. Similar considerations about the T cost driver (machining cost) lead to the conclusion that the use of 15 different classifications for the die typology is redundant. In fact, about half of the dummy variables are very close to the same value (equal to 2).

With regard to the significance of the quadratic influences of the cost drivers, they are attributed to numerical reasons since all driver effects were linearized during the dummy variable assignation. This represents an example of an unreal model behaviour that can be derived from the use of a parametric method for cost modelling. Anyway, their use

Table 4 Multivariate interpolations of the data and CER function

	Assembly/sheet bending			Machining/rubber injection		
	CER_{All}	CER_{Red}	CER	CER_{All}	CER_{Red}	CER
R^2	0.985	0.985	0.996	0.840	0.836	0.914
σ_e	0.0331	0.0331	0.0195	0.0638	0.0646	0.0458
Cost drivers						
Main (linear)	All	All		All	S, P, MD, T	
Interactions	All	$S*N$, $S*MD$, $S*LS$ $N*MD$, $N*LS$ $P*LS$		All	$P*T$	
Main (quadratic)	All	$P*P$ $MD*MD$		All	$P*P$	

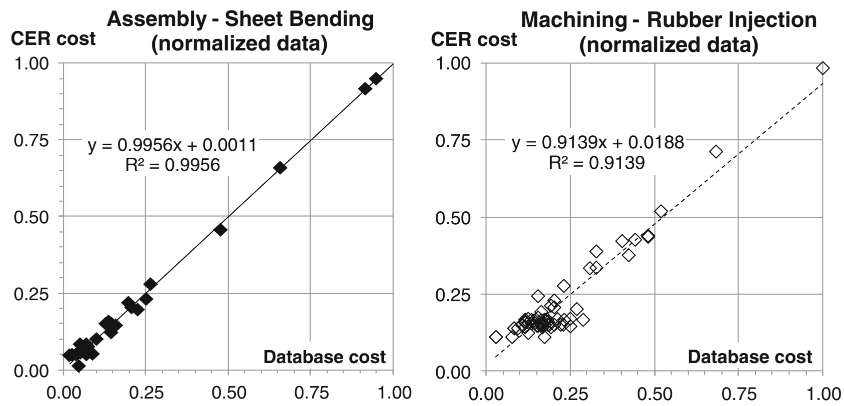


Fig. 7 CER result comparison with database

improves the results' accuracy and therefore, they were maintained in the CER function.

The overall results of the proposed method (Table 4, Figs. 7 and 8) show that it allowed to estimate two CER functions characterized by a high accuracy for both the manufacturing and machining operations. In fact, the comparison between the results of the two models and the available cost data shows a very high correlation (R^2 values close to 1), and the error is small and uniformly distributed as confirmed by the σ_e and p values in residuals plots. Moreover, the method allowed the use of data characterized by very high dispersion and non-uniformity. Amongst the two CER functions, the machining one shows a lower accuracy which can be derived from the scattering in the S values (Fig. 4) or in the initial data.

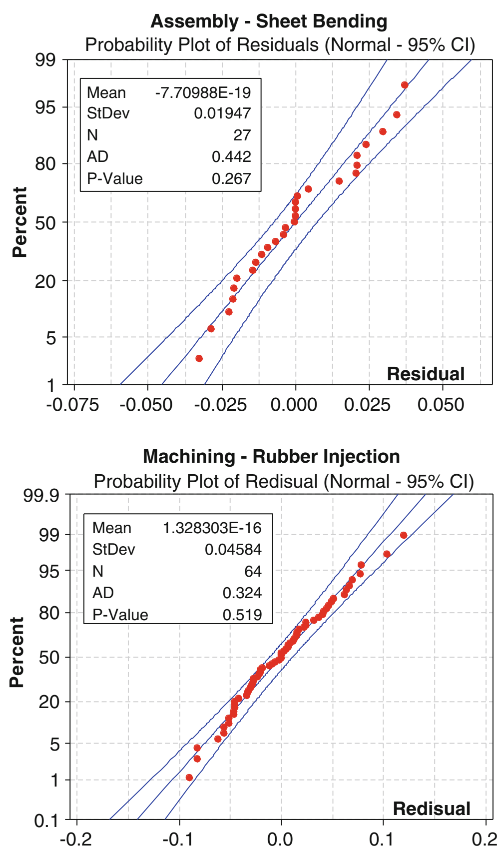


Fig. 8 Residuals of the CER function. Red circle represents the values of the residuals of the models. Blue lines refers to the 95 % Confidence Interval for a Gaussian distribution

4 Conclusions

In a market where products become obsolete in short time and require low lead time, time to market and manufacturing cost, it is important to correctly evaluate the product costs starting from the preliminary phases of its production cycle.

Net shape technologies are able to respond to the market requests, but the dies involved in the processes can represent a significant part of the final product cost. Literature proposes some models for estimating the manufacturing cost of dies but they are mainly based on analytical approaches. Therefore, they require detailed information that is available during the advanced phases of the product and manufacturing process development. Otherwise, parametric methods are suitable for cost estimations in the preliminary phase since they require few and generic cost drivers for their implementation.

For this reasons, the present study proposed a method based on cost drivers to estimate the cost of the manufacturing phases of the die.

The method was implemented using cost data related with die manufacturing, leading to the definition of two CER functions that are able to estimate the cost of assembly and machining phases. In particular, a procedure was presented to define a CER function using data that are organized according to the company's own criterion and that cannot be analyzed using variance analysis techniques. In fact, data were both numerical and textual, and they were not balanced and were characterized by a high and non-uniform variance. Therefore, when introducing specific cost drivers, it is possible to use information on the die's main dimensions that were stored using non-uniform ranges. Moreover, a procedure to introduce numerical dummy variables to substitute textual parameters was shown.

The results of the methods showed a high accuracy in cost estimations in spite of the high scattering of the initial data.

The evaluation of the cost driver impacts on the final cost suggested further strategies for both the drivers' definition and cost reduction.

Since the proposed model was implemented starting from generic and raw data regarding the dies and using multivariate regression techniques, it does not require a long-time analysis, specific tools or resources for its implementation. Moreover, it can be applied to different realities having their own data storage criteria and can be used starting from the preliminary phases of the die development or for quotations. Furthermore, it can be implemented in conjunction with other manufacturing policies of the company, to compare different solutions for the product quality [15] or production rate [16] improvements.

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References

1. Altan T, Lilly B, Yen YC (2001) Manufacturing of dies and molds. Ann CIRP 50(2):535–555
2. Bouaziz Z, Ben Younes J, Zghal A (2006) Cost estimation system of dies manufacturing based on the complex machining feature. Int J Adv Manuf Technol 28:262–271
3. Graziadei G (2004) Gestione della produzione industriale. Strumenti e applicazioni per il miglioramento della performance. Ed. Hoepli S.p.a, Milano (Italy). ISBN 9788820333959
4. Freiman FR (1983) The fast cost estimating models. AACE Transactions G.5, Philadelphia
5. Farineau T, Rabenasolo B, Castelain JM, Duverlie P (2001) Use of parametric models in an economic evaluation step during the design phase. Int J Adv Manuf Technol 17:79–86
6. Aamodt A, Plaza E (1999) Case-based reasoning: foundational issues. Methodological variations and system approaches. AI Commun 7(1):39–59
7. Duverlie PJ, Castelain M (1999) Cost estimation during design step: parametric method versus case based reasoning method. Int J Adv Manuf Technol 15:895–906
8. Creese RC, Adithan M, Pabla BS (1992) Estimating and costing for the metal manufacturing industries. Dekker, New York
9. Anthony RN, Hawkins DF, Merchant KA (1998) Accounting: texts and cases. Ed McGraw Hill/Irwin, New York. ISBN 9780073100913
10. Anthony RN, Hawkins DF, Macrì DM, Merchant KA (2008) Sistemi di controllo. Analisi economiche per le decisioni aziendali. Ed. McGraw Hill. ISBN 9788838667244
11. Wang H, Zhou XH, Ruan XY (2003) Research on injection mould intelligent cost estimation system and key technologies. Int J Adv Manuf Technol 3:215–222
12. Kazmer D (2007) Injection mold design engineering. Hanser Gardner Publications, Cincinnati (OH). ISBN 9781569904176
13. Boothroyd G, Dewhurst P, Knight WA (2011) Product design for manufacture and assembly. CRC, Boca Raton. ISBN 1420089277
14. Nagahanumaiah, Ravi B, Mukherejee NP (2005) An integrated framework for die and mold cost estimation using design features and tooling parameters. Int J Adv Manuf Technol 26:1138–1149
15. Sharma S (2010) Policies concerning decisions related to quality level. Int J Prod Econ 125(1):146–152
16. Sharma S (2011) Effects concerning quality level with the increase in production rate. Int J Adv Manuf Technol 53:629–634