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ON THE RIGHT APPROACH TO SELECTING A QUALITY IMPROVEMENT PROJECT IN MANUFACTURING INDUSTRIES

Continuous improvement is the core of any successful firm. Talking about manufacturing industries, there is huge potential for continuous improvement to be made in various work areas. Such improvement can be made in any section of industry in any form such as quality improvement, waste minimization, system improvement, layout improvement, ergonomics, cost savings, etc. This case study considers an example of a manufacturing firm which wanted to start a quality improvement project (QIP) on its premises. Various products were available, but with dwindling quality levels. However, the real task was the choice of a product for upcoming QIP, as it is well known that success heavily depends upon the selection of a particular project. This is also because of the amount of effort in terms of time, money and manpower that is put into a project nowadays. The authors' objective was to compare three techniques, namely, cost of poor quality (COPQ), conditional probability and fuzzy TOPSIS for selecting the right project based on this specific firm. The pros and cons of these approaches have also been discussed. This study should prove to be instructive for the realization of QIPs in similar types of industry.

Keywords: *cost of poor quality* (*COPQ*)*, decision tree, Bayes' theorem, fuzzy TOPSIS, project selection*

1. Introduction

Nearly 70% of projects are subject to cost-overruns or are not accomplished on schedule due to poor planning, poor communication or poor resource distribution. The

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major causes of project failure in manufacturing industries include: improper project staffing, inexperienced staff, mismanagement of data, inability to define the scope of a project, unreasonable deadlines, a lack of communication among employees and the most common, inappropriate project selection. Hence, failure can be defined as obtaining fewer benefits than anticipated. Project selection is a part of any strategic management framework and there are various mathematical methods of decision-making available and applied for this purpose. Major flaws in many of these techniques include their incapability to consider various tactical factors and their mathematical intricacies [1]–[3]. There are also some risks that are involved in project selection. These risks are more concerned with the successful achievement of fundamental objectives than others such as risks regarding costs, scheduling and deadlines. If such risks are present, then obviously, they should be fully understood before selecting a particular project.

In manufacturing industries, various quality improvement projects (QIPs) are initiated for the purpose of improving product quality or the production process. Project selection in these types of industries often corresponds to selecting a part/product on which the team should work. The basic technique for selecting a project is to calculate the rejection percentage. In many firms, experienced personnel generally use their instinct and some simple statistics describing the rejection percentage of various products being manufactured there. Another technique that is in use is to calculate the cost of poor quality (COPQ). Under this approach, the COPQ is estimated and the one with its highest value is given preference in project selection. Although these methods are very basic and old, they are still in use by many small scale firms across the world. The point of concern with these methods is that they only use historical data in terms of the rejection percentage and COPQ and bypass any possible future complicacy. If such a situation arises, the whole effort that is being put into improving the quality level of a particular product is going to be in vain. This can be a huge financial, as well as motivational setback for a firm. Therefore, a technique that uses both the historical and projected future trend can be very helpful. A common approach to this problem is to integrate Bayes' theorem and decision tree analysis. This method, also known as the conditional probability analysis, uses expected efficacy as the criterion for identifying the ideal alternative and ensures that complex decisions will avoid such unwanted characteristics as intransitivity of preferences [4]. Decision analysis is normative rather than expressive, as it provides a methodological approach to making optimal decisions. Another common technique that is in use nowadays is fuzzy logic with multiple attribute decision making (MADM). This approach is used when a decision is to be made among several alternatives on the basis of a number of parameters. A real time case has been selected for project selection using the techniques mentioned above. A brief description of these approaches is given in the following section.

2. About the tools

2.1. The cost of poor quality

This is a common and the easiest to use tool for quantifying qualitative improvements in an organization. Costs related to quality can be categorized into two groups (Table 1): costs related to poor quality and costs incurred to improve quality. Examples of the latter category are prevention costs and appraisal costs. The former category includes the costs of product failure [5]. Calculating the COPQ significantly affects the process of decision making. A reduction in costs related to quality leads to an increased profit.

Table 1. Categorization of the costs related to quality

Costs of improving quality	Costs of poor quality
Prevention costs	Internal costs
Marketing costs	Costs of design failure
Planning costs	Purchasing failure
Training costs	Operational costs
Appraisal costs	External costs
Purchasing costs	Costs of customer service
Costs of trials	Returned goods costs
Test and inspection costs	Costs of warranty claims

The COPQ can be calculated by defining the cost of a product at various stages of production and then multiplying such a cost by the appropriate rejection rate at that stage [6]. Adding up all these costs together with the additional costs of development, depreciation and maintenance ultimately provides the total COPQ. When selecting a project for quality improvement, the product with the highest COPQ is selected as this maximizes the scope for improvement and savings.

2.2. Bayes' theorem and decision tree analysis

Bayes' theorem. A Bayesian approach is a truly powerful tool for many theoretical and practical problems. It defines probability as the level of certainty related to a potential outcome [7]. Bayes' theorem is a result in the probability theory that computes and compares conditional probabilities. A key use of Bayes' theorem is to appraise or revise the strengths of evidence-based opinions in the light of new evidence a posteriori. According to Bayes' theorem

$$P\left(A|B\right)=\frac{P\left(B|A\right)P\left(A\right)}{P\left(B\right)} \tag{1}$$

where $P(A)$ and $P(B)$ are the prior or marginal probabilities, $P(A|B)$ and $P(B|A)$ are the conditional probabilities. These are also known as posterior probabilities because they are derived for a given realization of the second variable.

A Bayesian approach can be used effectively in the area of decision making under uncertainty, where conditional probabilities for future states given the present state are to be dealt with. The use of Bayes' theorem in the environment of the manufacturing sector occurs when conditional probabilities naturally arise in a production process and a solution has to take into account the probability of success at each stage. Bayes' theorem has been applied effectively in various types of problems related to optimization [8], reliability analysis [9], decision support systems [10], forecasting [11], etc.

Decision tree analysis. A decision tree can be compared to a flowchart in which various nodes are present. The inner nodes denote a test on an attribute, a branch denotes the result of thea test and each leaf node characterizes a class label. The routes from root to leaf represent classification rules. In the decision analysis, decision trees and closely related influence diagrams are used as a visual and analytical decision support tool, where the expected values (or expected utility) of competing alternatives are calculated. Decision trees are frequently used in operations research, specifically for decision analysis, in identifying a strategy to attain a specified goal. Decision tree analysis has been successfully applied in the area of making an appropriate choice, whether it is site selection [12], machine tool selection [13], vendor selection [14], process selection [15], etc. Also, in some cases a decision tree has been used in combination with Bayes' theorem for better results [16].

2.3. Fuzzy multiple attribute decision making approach

MADM techniques are used when a decision is to be made from a number of alternatives in the presence of many parameters. The current case study is such an example, where a project has to be selected from various choices and selection is dependent on a number of variables.

Table 2. Some examples of using fuzzy and TOPSIS in project selection scenarios

No.	Authors	Year	Description
1	Karsak and Talga [17]	2001	selection of the most suitable advanced manufacturing system
2	Al-Najjar and Alsyouf [18]	2003	optimal choice of a maintenance systems
3	Kahraman et al. [19]	2007	selection of a logistics system
4	Onut et al. [20]	2009	selection of a suitable equipment for handling material
5	Rao, Patel [21]	2010	selection of materials
6	Vats, Vaish [22]	2013	selection of piezoelectric materials
7	Rathi et al. [23]	2016	selection of six sigma project
8	Mittal et al. [24]	2016	ranking problems of a plywood producer

Therefore, the comparison drawn between various approaches to project selection will be incomplete without describing this approach. Often fuzzy logic is applied together with MADM techniques to model the fuzziness and uncertainty existing in the process. Various MADM approaches are available but, depending upon the nature of a problem, technique for order preference by similarity ideal solution (TOPSIS) may be described as a MADM approach. A literature review (Table 2) also suggests that TOPSIS gives the best solution to similar types of problems. Here is a brief introduction to these two approaches.

Fuzzy logic. Fuzzy logic was introduced by Zadeh in 1965 [25] to model situations and variables where uncertainty occurs [26]. It deals with variables which cannot be precisely defined in quantitative terms and problems where it is very challenging to find an outcome because of the presence of a number of alternatives, together with a number of parameters affecting them [27]. A fuzzy approach can be combined with a suitable MADM technique in the cases where the likelihood of an event is not precisely known [28]. Fuzzy logic is based on set theory and defines a membership function on the interval (0, 1). Such a membership function designates the significance of an element as a member of the appropriate set [29]. Although various types of membership functions are available: such as triangular, trapezoidal, Gaussian, etc., their use depends upon the nature of the problem and the type of data available. Linguistic variables with preassigned numerical values are used for all of the assessments. The values of these variables are centred on the rating given in a standard or artificial language [30]. Extensive use of such a linguistic approach has been noted in various fields, such as artificial intelligence, human decision processes, pattern recognition, psychology, brain research, economics and related areas [31]. There are many case studies in the literature demonstrating the successful use of Fuzzy MADM in decision making [32–36].

The TOPSIS method. The TOPSIS is a MADM technique that was first proposed by Hwang and Yoon in 1981 [36, 37]. It is one of the classical methods used to solve MADM problems by identifying the solution from a finite set of alternatives. It is a calculation technique based on strong logical principles that can be easily applied in practical decision making. It also defines favourites and provides an index that indicates the best and the worst options [38]. TOPSIS proscribes positive and negative ideal solutions to resolve MADM problems [39]. The former increase earnings by limiting costs and vice-versa [40]. A lot of case studies on project selection using the TOPSIS approach have been reported in the literature [41, 42].

Detailed steps involved in a fuzzy TOPSIS methodology This section describes the steps involved in a fuzzy TOPSIS approach to project selection. Modified digital logic (MDL) is used to calculate the weight of all the parameters. The steps included are as follows;

Step 1. *Calculation of MDL weights*. First of all, MDL weights (W_j) are calculated for the parameters using the following equation. Based on the experts opinion, a decision matrix is formed for a pair-wise comparison. Experts assign 1, 2 and 3 for less, equal or more important parameters P_j, respectively.

$$W_j = \frac{P_j}{\sum_{j=1}^{n} P_j} \tag{2}$$

Step 2. *Description of linguistic variables, membership function and equivalent fuzzy numbers.* A set of fuzzy values is necessary to compare all the alternatives according to each criterion. These fuzzy terms are assigned by the decision-makers and used for intra criterion comparisons of the alternatives.

Step 3. *Construction of a decision matrix*. Let p be the number of parameters, q be the number of alternatives and k the number of decision makers/team members in the modelled decision process. The totalled fuzzy rating according to the criterion C_j is denoted by $x_{ijk} = \{x_{ijk1}, x_{ijk2}, x_{ijk3}, x_{ijk4}\}$. For $i = 1, 2, ..., p$; $j = 1, 2, ..., q$ and $k = 1, 2, ..., k$, the x_{ijk} are calculated as in [33, 43]:

$$\left\{ \begin{array}{l} x_{ij1} = \min_k \{b_{ijk1}\} \\ x_{ij2} = \frac{1}{k} \sum b_{ijk2} \\ x_{ij3} = \frac{1}{k} \sum b_{ijk3} \\ x_{ij4} = \min_k \{b_{ijk4}\} \end{array} \right\} \tag{3}$$

Thus the decision matrix obtained $\mathbf{Z}$ is:

$$\mathbf{Z} = \begin{bmatrix} x_{11} & x_{12} & ... & x_{1p} \\ x_{21} & x_{22} & ... & x_{2p} \\ ... & ... & ... & ... \\ x_{q1} & x_{q2} & ... & x_{qp} \end{bmatrix} \tag{4}$$

Step 4. *Defuzzification*. Defuzzification is a technique for translating the non-numeric realizations of fuzzy variables into numeric crisp values assessing each alternative according to each criterion. The input for this procedure is the cumulative set and the output is a single number. The following equations lead to the appropriate crisp values:

$$f_{ij} = \text{Defuzz}\left(x_{ij}\right) = \frac{\int u\left(x\right) x dx}{\int u\left(x\right) dx} A = \pi r^2 \tag{5}$$

$$f_{ij} = \frac{\int_{x_{ij1}}^{x_{ij2}} \left(\frac{x - x_{ij1}}{x_{ij2} - x_{ij1}}\right) x dx + \int_{x_{ij2}}^{x_{ij3}} x dx + \int_{x_{ij3}}^{x_{ij4}} \left(\frac{x_{ij4} - x}{x_{ij4} - x_{ij3}}\right) x dx}{\int_{x_{ij1}}^{x_{ij2}} \left(\frac{x - x_{ij1}}{x_{ij2} - x_{ij1}}\right) dx + \int_{x_{ij2}}^{x_{ij3}} dx + \int_{x_{ij3}}^{x_{ij4}} \left(\frac{x_{ij4} - x}{x_{ij4} - x_{ij3}}\right) dx}$$

$$= \frac{-x_{ij1} x_{ij2} + x_{ij3} x_{ij4} + \left(\frac{1}{3}\right)\left(x_{ij4} - x_{ij3}\right)^2 + \left(\frac{1}{3}\right)\left(x_{ij2} - x_{ij1}\right)^2}{-x_{ij1} - x_{ij2} + x_{ij3} + x_{ij4}} \tag{6}$$

Step 5. *Normalization and weighted normalized decision matrix*. The normalization matrix is obtained from the following equation:

$$r_{ij} = \frac{f_{ij}}{\sqrt{\sum_{i=1}^{m} \left(f_{ij}\right)^2}} ; \forall_j \tag{7}$$

The equation for calculating the weighted normalized decision matrix is as follows:

$$V_{ij} = \left[r_{ij}\right]_{mn} \left[W_j\right]_{nm}^{\text{diagonal}} \tag{8}$$

Step 6. *Ideal solutions.* The positive and negative ideal solutions are calculated. The equations for calculating the positive ideal solution V_j^+ and the negative ideal solution V_j^- are as given below:

$$V_j^+ = \left\{\left(\max V_{ij},\ j \in j_1\right), \left(\min V_{ij},\ j \in j_2\right), i = 1, 2, 3, ...,\ m\right\}, \forall_j \tag{9}$$

$$V_j^- = \left\{\left(\min V_{ij},\ j \in j_1\right), \left(\max V_{ij},\ j \in j_2\right), i = 1, 2, 3, ..., m\right\}, \forall_j \tag{10}$$

where j_1 and j_2 represent the set of variables where the highest values and the lowest values are best, respectively.

Step 7. *Calculating the distance from an ideal one.* The equations for calculating the distances d_i^+ and d_i^- from the positive ideal solution and the negative ideal solution, respectively, are given by

$$d_i^+ = \sqrt{\sum_{j=1}^{n}\left(V_{ij} - V_j^+\right)^2},\ i = 1, 2, 3, ..., m \tag{11}$$

$$d_i^- = \sqrt{\sum_{j=1}^{n}\left(V_{ij} - V_j^-\right)^2},\ i = 1, 2, 3, ..., m \tag{12}$$

Step 8. *Calculating of the TOPSIS index*:

$$C_i^+ = \frac{d_i^-}{d_i^- + d_i^+} \tag{13}$$

Ranking is performed in descending order of the C_i^+ indices.

3. Case study findings

The firm considered wanted to start up a QIP but was unsure which product would lead to the maximum monetary yield. This firm has a turnover of INR 4.5 billion and thus comes under the category of small and medium size enterprises (SME). The firm has two units, one is a die-casting facility and the other is a piston and swashplate manufacturing unit. The major products of the firm consist of various types of die-casted brackets and auto air-conditioning, pistons and swashplates. These products are installed in various automobiles. Brackets are used for mounting engines and pistons and swashplates are used in auto air-conditioning units. The shop floor of the die-casting unit is equipped with 4 (800 tonne capacity) horizontal clamping vertical squeeze casting (HVSC) machines, 2 (850 tonne capacity) high pressure diecasting (HPDC) machines, 2 (150 tonne capacity) low pressure diecasting (LPDC) machines, 10 vertical machining centre (VMCs), a shot blasting machine and an impregnation and infiltration setup. In the piston and swashplate unit, the piston manufacturing line consists of a special purpose machine (SPM) (centring and facing), CNC (turning), centreless grinder, Teflon coating machine, SPM (end cutting), and CNC (ball pocket cutting). The swash-plate manufacturing line consists of an SPM (Takisawa) tin coating machine, CNC (super finishing). The firm supplies parts to a number of reputed overall equipment manufacturers (OEMs) worldwide. Despite having the best machinery in the region, the firm was facing the problem of a huge rejection rate for many of its products, so a QIP was the need of the hour. However, the first step was to select a product to which QIP could be applied. Therefore, a list of various models of pistons was prepared for the purposes of selection. The three techniques discussed above were implemented and the results were very surprising.

4. Results and discussion

4.1. Project selection by calculating the cost of poor quality

Firstly, the COPQ technique was used for project selection. As per the procedure, the current production and rejection levels of the initially selected pistons were noted. After that, the costs[2] of these models of piston at various major stages of production, as well as the final costs were listed. Tables 3–5 illustrate the analysis of the current costs for each piston at various stages of production.

Table 3. Cost of manufacturing pistons at various stages of production

Part No.	Model	Cost/piece	Cost/piece at major stages of inspection		
			Diecasting	Machining	Final inspection
11651k00	Maruti 800	132	79	112	125
11632k00	Alto 800	165	99	140	157
11749k00	Swift	309	185	263	294
11641k00	Wagon-R	195	117	166	185
11650k00	Tata Nano	82	49	70	78

Table 4. Rejection rate of pistons at various stages of production

Part No.	Model	Current production	Number rejected	Rejection at major stages of inspection		
				Diecasting	Machining	Final inspection
11651k00	Maruti 800	11 228	1082	715	322	45
11632k00	Alto 800	286 695	21 311	15 386	4683	1242
11749k00	Swift	400 161	11 205	8203	2161	840
11641k00	Wagon-R	203 385	14 173	10 423	2034	1716
11650k00	Tata Nano	23 642	3881	2683	946	252

Using these data, the total COPQ was calculated. It can be seen that product No. 11632k00 had the highest COPQ. So it should be selected as a project for quality improvement, since it is assumed that the scope for improvement is highest for this product. This technique relies only on historical data and no weights are given to future trends.

[2] All costs in INR.

Table 5. Cost analysis of pistons at various stages of production

Part No.	Auto-Model	COPQ			Total per annum
		Diecasting	Machining	Final inspection	
11651k00	Maruti 800	56 616	36 114	5632	98 362
11632k00	Alto 800	1 523 211	656 747	194 738	2 374 695
11749k00	Swift	1 520 892	567 552	246 681	2 335 126
11641k00	WagonR	1 219 547	337 111	317 900	1 874 558
11650k00	Tata Nano	132 022	65 914	19 645	217 580

4.2. Project selection using Bayes' theorem and decision tree analysis

As the products of the firm under consideration were to be used in different models of automobiles, first of all a market survey was performed to estimate the trend in global automotive sales (Fig. 1).

Fig. 1. Sales data of various vehicles from 2005 to 2015. Source: ACG, MNT Research Group. Production of Maruti 800 discontinued after 2014. Production of Tata Nano started in 2009

There are various agencies available that forecast trends in global sales and these include ACG, MNT Research Group etc. The historical trends of sales of the parent models were also noted for our reference (Fig. 1). Except Maruti 800 and Tata Nano, these models of automobiles show an increasing trend in terms of sales. The Maruti 800 was discontinued in 2014 and the Tata Nano, except for some initial success, could not attract consumers. But the overall global market trend suggests an increase in automobile sales in the coming years.

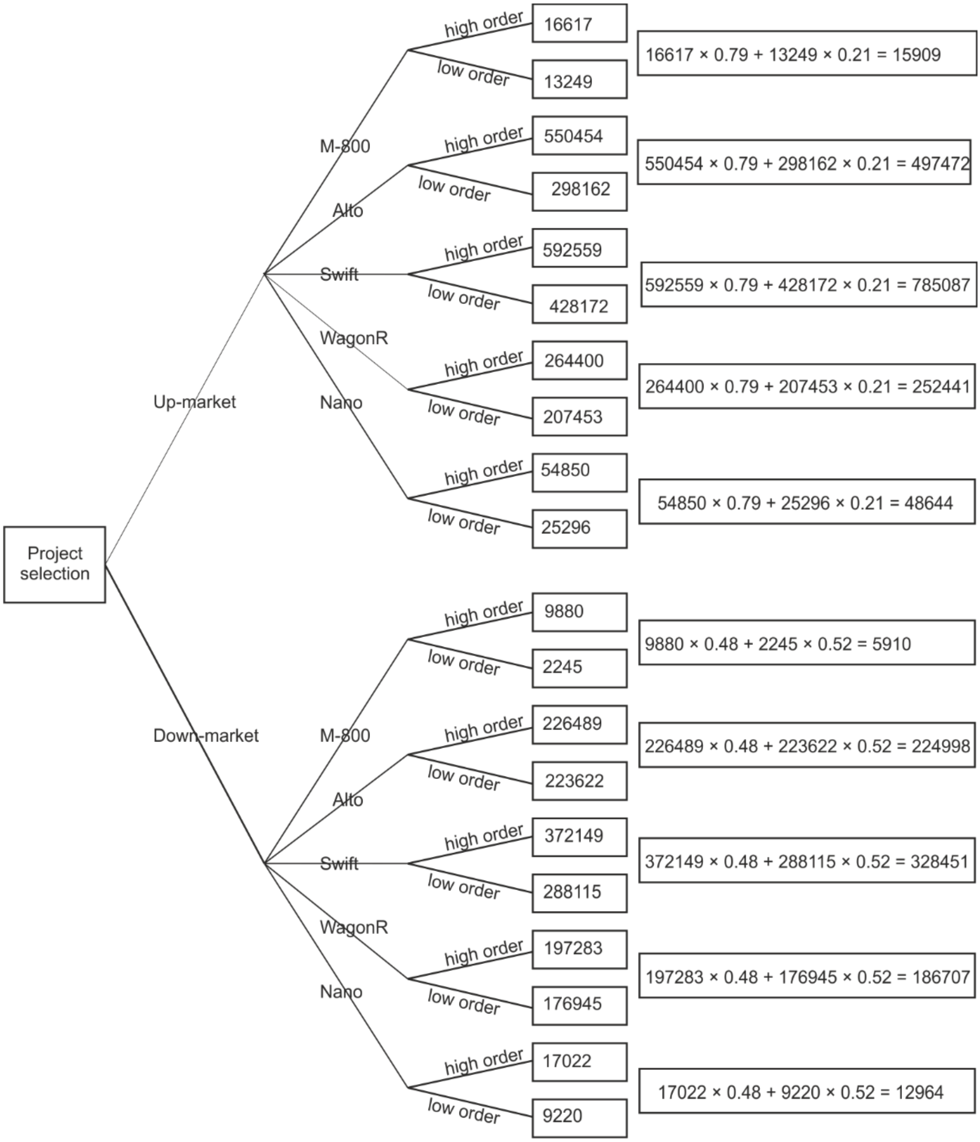

Fig. 2. Decision tree analysis

Also, as a part of the development process, the customers (OEMs) provide forecasts of future demand to suppliers (vendors), so data on past and future demand were considered for analysis. Also, the firm's medium term plans were considered in predicting the future sales of various parts. After that, probabilities were assigned to possible future trends in the global automobile market. Conditional/posterior probabilities were also assigned for various products according to their parent model. A decision tree (Fig. 2) was constructed, which presents these probabilities at each level for each product and then the percentage change of sales with respect to the previous year was calculated for each model. Given an optimistic prediction of total global sales, for a particular product the greatest positive change multiplied by the current production gives the high level of orders and similarly the lowest positive change multiplied by current production gives the low order quantity. A similar rule was applied to derive the high and low order quantities for a pessimistic prediction of the global trend in sales.

Let m_1 = up market, m_2 = down market, v_1 = high number of orders, and v_2 = low number of orders. The probability of up-market is 70% ($P(m_1) = 0.7$), the probability of down-market is 30% ($P(m_2) = 0.3$).

If it is an upmarket, then the chances of a high number of orders are 80% ($P(v_1/m_1) = 0.8$, $P(v_2/m_2) = 0.2$).

If it is a down market, then the chances of a high number of orders are 50% ($P(v_1/m_2) = 0.5$, $P(v_2/m_2) = 0.5$).

Step 1. The conditional probabilities for the number of orders given the state of the market $P(v_j/m_i)$ in this problem can be summarized as:

	V_1	V_2
M_1	0.8	0.2
M_2	0.5	0.5

Step 2. Compute the joint probabilities for the state of the market and the number of sales as:

$$P(m_i, v_j) = P\left(\frac{v_j}{m_i}\right) P(m_i) \text{ for all } i \text{ and } j$$

	V_1	V_2
M_1	0.56	0.14
M_2	0.15	0.15

Step 3. Compute the marginal probabilities for the number of sales as:

$$P\left(v_j\right)=\sum_{alli}^{n} p\left(m_i,v_j\right) \text{ for all } j$$

$P(v_1)$	$P(v_2)$
0.71	0.29

Step 4. Determine the desired posterior probabilities for the state of the market given the level of sales as:

$$P\left(m_i/v_j\right)=\frac{P\left(m_i,v_j\right)}{P\left(v_j\right)}$$

	V_1	V_2
M_1	0.79	0.48
M_2	0.21	0.52

Table 6. Expected savings for pistons at various stages of production

Part No.	Model	Production up market	Production down market	Savings up market	Savings down market
11651k00	Maruti 800	15 909	5910	139 369	51 774
11632k00	Alto 800	497 472	224 998	4 120 561	1 863 658
11749k00	Swift	795 037	328 451	4 639 411	1 916 664
11641k00	WagonR	252 441	186 707	2 326 697	1 720 840
11650k00	Tata Nano	48 643	12 954	447 668	119 217

Based on their current production and rejection levels, the cost of poor quality was estimated for each of the products. Applying a Bayesian approach to the decision tree gives the quantity of each product that do not meet quality standards. A series of calculations (Fig. 2) gave the amount of money that could be saved by selecting a particular product for the upcoming project. Therefore, the product associated with the highest savings should be chosen, which comes out to be 1174968k00 (to be used in the Maruti Swift) in this case (see Table 5). Now it can be seen that appropriate weights have been given to future trends along with the historical data.

4.3. Project selection using a fuzzy TOPSIS approach

In the third part of our study, project selection was performed using a fuzzy TOPSIS approach. Using this perspective, first of all, the important parameters significantly affecting selection of a project were listed. They are given in Table 7 along with their sub-parameters.

Table 7. Parameters and sub-parameters

No.	Parameter	Code	Sub Parameters
1	historical rejection level (HRL)	C1	history of rejections and improvements made /tried in the past
2	feasibility of modifications (FOM)	C2	feasibility in terms of the space and assets required for modifications
3	future growth perspective (FGP)	C3	future demand, market scenario
4	development cost (DC)	C4	cost of modifying the process, cost of earlier development
5	expected savings (ES)	C5	share in total costs resulting from poor quality

The parameters listed above were chosen after rigorous brainstorming sessions performed with the managers of various departments within the firm. These parameters included consist of the historical rejection level, which directly affects the loss to the firm; the feasibility of modifications, which includes the viability and practical aspects of making any change in the process; the future growth perspective, which includes the anticipated future scenario describing sales of a particular part; development costs, which include the cost of any change in the process, be it the purchase of additional machines or modifications in the layout of the plant or labour costs etc., expected savings, which include the overall monetary benefits expected after completion of project.

Table 8. Calculation of weights using MDL

Parameter	C1	C2	C3	C4	C5	Positive decisions	Weight	Rank
HRL	2	3	3	1	1	8	0.200	1
FOM	1	2	3	3	1	8	0.200	1
FGP	1	1	2	3	3	8	0.200	1
DC	3	1	1	2	3	8	0.200	1
ES	3	3	1	1	2	8	0.200	1

The steps described above were followed. Modified digital logic (MDL) was used to derive the weight of each parameter. The values obtained are shown in Table 8. It is evident from this table that each parameter was equally important in project selection as the weight of each parameter is the same.

Now, linguistic variables were assigned to each product as per their importance with respect to each parameter as shown in Table 9 (for the definition of the linguistic variables see Table 10). For example, the historical rejection level for 11650k00 and 11651k00 was on the low side as compared to other parts; 11632k00 had the highest value in this regard. Therefore, the appropriate fuzzy linguistic variables are assigned as visible from Table 9. A similar approach was followed and the values of linguistic variables corresponding to each parameter were assigned to each alternative.

Table 9. Assigned linguistic variables

Alternative	HRL	FOM	FGP	DC	ES
11650k00	VL	A	AA	EL	VL
11651k00	VL	VH	EL	A	EL
11641k00	VH	EL	AA	AA	VH
11749K00	VH	EH	EH	AA	EH
11632k00	EH	EL	AA	AA	VH

Although various types of fuzzy numbers can be used depending on the situation, in the present case we used trapezoidal fuzzy numbers (TFN) (b_1, b_2, b_3, b_4) for {b_1, b_2, b_3, $b_4 \leq \in R$, $b_2 \leq b_3 \leq b_4$} (Fig. 3). This is because of their simplicity and information processing in a fuzzy environment [44]. The membership function $\mu_b(x)$ for a TFN is defined as:

$$\mu_b(x) = \begin{Bmatrix} \dfrac{x-b_1}{b_2-b_1}, \ x \in [b_1, b_2] \\ 1, \ x \in [b_2, b_3] \\ \dfrac{b_4-x}{b_4-b_3}, \ x \in [b_3, b_4] \\ 0, \text{ otherwise} \end{Bmatrix} \tag{14}$$

Table 10. Fuzzy numbers corresponding to values of the linguistic variables

Linguistic variable	Fuzzy number
Exceptionally high (EH)	(0.8, 0.9, 1.0, 1.0)
Very high (VH)	(0.7, 0.8, 0.8, 0.9)
High (H)	(0.5, 0.6, 0.7, 0.8)
Above average (AA)	(0.4, 0.5, 0.5, 0.6)
Average (A)	(0.2, 0.3, 0.4, 0.5)
Very low (VL)	(0.1, 0.2, 0.2, 0.3)
Extremely low (EL)	(0, 0, 0.1, 0.2)

Fuzzy numbers are assigned to each value of the linguistic variable as shown in Table 10. This is usual practice for the purposes of further calculation. The fuzzy numbers defined here are standard TFNs.

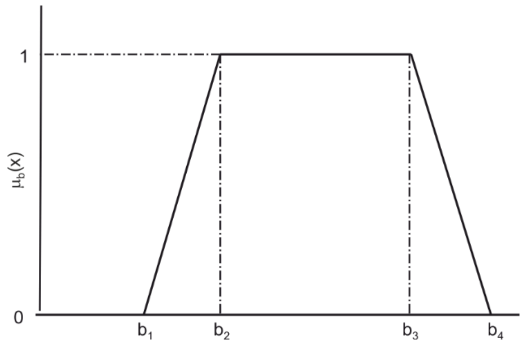

Fig. 3. Trapezoidal fuzzy numbers

With the help of fuzzy numbers, the qualitative results presented in Table 9 can be converted into the form of quantifiable crisp values for each product according to each parameter as per step 4 of 2.3.3. The values obtained are listed in Table 11.

Table 11. Crisp values

Alternative	HRL	FOM	FGP	DC	ES
11650k00	0.2333	0.3667	0.5333	0.0778	0.2333
11651k00	0.2333	0.8333	0.0778	0.3667	0.0778
11641k00	0.8333	0.0778	0.5333	0.5333	0.8333
11749K00	0.8333	0.9444	0.9444	0.5333	0.9444
11632k00	0.9444	0.0778	0.5333	0.5333	0.8333

Further calculations, as per the steps discussed in Section 2.3.3, resulted in the TOPSIS index, according to which a ranking was defined as shown in Table 12. It is evident from the table that 11749K00 was ranked as having the best prospective. It can be seen that the HRL of 11749K00 was not the highest. However, the contribution of other parameters resulted in this part obtaining the highest TOPSIS index.

Table 12. TOPSIS indices and ranks

Alternative	TOPSIS index	TOPSIS rank
11650k00	0.304	5
11651k00	0.392	4
11641k00	0.536	3
11749K00	0.945	1
11632k00	0.547	2

Now after obtaining the results from all three approaches described above, the real question is which one of these approaches is the best? The answer to this question is very complicated as there are many dependent factors. If we talk about the simplicity of an approach, COPQ is the simplest. It can be applied by a semi-skilled operator without any knowledge of statistics or data analysis. Therefore, if the applicability of an approach is the major concern in an SME where the workforce is semi-skilled, then COPQ is the best solution. However, one disadvantage is that it only uses historical data and does not take future trends into account.

In firms where the skill level of the workforce is not an issue and separate departments for forecasting have been set up and data analysts have been hired, they can use statistically advanced approaches like Bayes' theorem, decision tree analysis and fuzzy MADM. These approaches also take future expected trends into account, along with historical data, covering all the information available in the form of data. Further, among these approaches the fuzzy approach has an advantage, because using Bayes' theorem the conditional probability always talks about the probability of an event happening or not. The answer is either yes or no. When talking about probability, one is interested in whether an event will happen or not and in this regard you define a value in terms of the percentage chance of occurrence. However, fuzzy logic tries to capture the essential property of vagueness. Fuzzy logic is all about degrees of certainty. Combining MADM with a fuzzy approach allows us to make decisions more easily in the case of various alternatives that each depend on a set of parameters.

In the current study, fuzzy logic was used and 5 parameters were taken in to account. This number can be increased or decreased as per the viewpoint of an analyst or to take into account any unapprehended situation. However, using other approaches we cannot avail of this facility.

5. Conclusions

The authors presented the practical implications of three commonly used approaches to project selection and found that consideration of a blend of historical data and projections of future demand should be balanced, along with other parameters depending upon the product in question. A case study has been described in which the management of a firm wanted to start a QIP to improve productivity levels. The results provided by COPQ differ from those provided by Bayes' theorem and a fuzzy TOPSIS approach. This is because of two factors. One is the difference between the approaches of the techniques and the other is the factors included during implementation. Moreover, it can be stated that an appropriate approach is one which considers all the factors which have a significant direct or indirect influence on the costs related to poor quality prior to reaching any conclusion. In this study, the product 11749K00 was selected as the subject of a quality improvement project and after implementing the recommendations made by the QIP team, the firm achieved a huge improvement, both in terms of quality and monetary gains. This proves the importance of adopting an appropriate approach to project selection in manufacturing industries. This study could also give helpful indications to other firms with similar problems.

Conditional probability and fuzzy TOPSIS are modern approaches and are very capable of providing sound results, but these methods require a skilled workforce. Also, various other forms of these approaches are constantly emerging with an increased level of interest from researchers in this area.

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