ELSEVIER

Journal of Food Engineering 27 (1996) 311–322

0260-8774/96 $15.00+0.00

0260-8774(95)00013-5

Characterization of Mill Products by Analysis of In-flow Digitalized Images

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(Received 17 June 1994; revised version received 16 January 1995; accepted 23 March 1995)

ABSTRACT

A sensor has been designed and tested in a pilot mill to characterize granular products in the food industry. It consists of:

- *a mechanical system which takes a representative part of the product,*
- *a CCD camera to capture images,*
- *a software package for image analysis and data processing.*

The method consists of comparing a sample with a predetermined 'quality class'. The decision system is built on example learning: real cases fed into the system allow its configuration. Three quality classes have been defined, they correspond to the rolls gap (0·30, 0·40, 0·50 mm) of the first break rolls of a semolina pilot mill. In these conditions, the classification accuracy rate achieved by the system is higher than 80%.

INTRODUCTION

Cereal milling processes involve two distinct operation units, i.e. breaking and separation. The breaking of grains and mill products is carried out by machines fitted either with corrugated rolls (break and scratch rolls) or with smooth rolls (converters). The setting of these machines is of major importance from an economic point of view (milling yield) as well as for the commercial value of the finished products. In durum wheat milling, for instance, the most accurate control of the breaking and the scratching processes is necessary since the separation between the endosperm and the bran is meant to produce particles with a granulometry higher than 200 μm, flour being considered as a by-product. Therefore the regulation of rolls devices is conducted by the miller, a skilled craftsman who can make a clear assessment without depending only on measurements (granulometry analysis) but also on more difficult to quantify sensory observations such as vision and touch.

In the past few years, various aids to on-line regulation of the rolls devices have been provided. Some of these systems are designed for controlling the speed of the input rolls as a function of the loading of the machines and of the product output (McGee, 1982). Others have predefined settings of roll gaps as a function of the features of both wheat and required finished products (Gamperle, 1988). These adjustments are performed either manually or by remote control. More recent systems allow a feed-back control on the roll gap depending on the weight of the product required at the output of a plansifter (Berga, 1988). Such a system is unquestionably progress towards the automation of the milling process, nevertheless since only quantitative assessment is used, the measures are still far removed from the skilled gesture of the miller who can also evaluate the 'quality' of the breaking.

In order to determine the morphologic characteristics of individual whole grains, image analysis has been used (Sapirstein *et al.*, 1986; Devaux *et al.*, 1991). A method was proposed for classifying populations so as to predict the granulometry class of mill products analysed in heaps and based on their textural features (Bertrand *et al.*, 1991). The results obtained, although encouraging, were not sufficiently accurate to allow a wide industrial application of the technique (Bertrand *et al.*, 1993). The purpose of this paper is to present a system able to characterize on-line, by image analysis, objects that cannot be modeled owing to their irregular shape, such as mill products. A novel data processing method has been designed to take into account the geometric characteristics of the particles as well as the global, mainly textural, features of the population as a whole. Images of a sample being milled are related to a predetermined quality class. Among the available analysis methods, artificial vision has been chosen because it does not involve any hypothesis about the shape of the particles while allowing a wide range of particle size and can take into account complementary features such as shape, colour and texture. The technique is compatible with real-time constraints, i.e. it is quick, repeatable and sufficiently accurate. On line, to avoid preparing the sample, the images can be captured in-flow while the process is in progress (Sinfort *et al.*, 1992). This time-saving method does not provide any sorting. In this paper, a description of the materials and the classification methods will be given and will be followed by the intrinsic performance of the sensor together with the results obtained in an on-line pilot mill.

MATERIALS AND METHODS

1. The pilot mill

The breaking trials were carried out in the INRA semolina pilot mill (Abecassis *et al.*, 1987) which is designed for storing, cleaning, tempering and milling wheat (capacity 150 kg/h). The mill consists of nine roller mills:

five breakers and four scratch rolls; three plansifters forming eight sifting sections and three double purifiers with two stacked tables. The handling of the mill products is performed by two pneumatic circuits.

The first breaking stage was selected for the trials as the main differences in the milling behaviour of grain usually appear during the first stages of the breaking, thus requiring a precise adjustment of the settings. The original lay out of the pilot mill breaking head, now widely adopted throughout Europe, is designed so that the grain passes through two successive rolls devices (length=200 mm, diameter=150 mm) without intermediate sifting. The first break roll (B1) is designed to shear the grain while the second (B2) starts the process of separation between the endosperm and the bran.

The mill was loaded with a durum wheat batch (commercial blend from the south of France, 1990 crop) which had been cleaned and tempered up to 17% moisture content for 3 h prior to the milling. The grains were crushed in the above mentioned conditions. The feeding rate was the usual flow of the mill: 130 kg/h. The setting of the first break roll was kept constant (roll-gap: 0·70 mm) while the gaps of the second one was set successively at 0·30, 0·40 and 0·50 mm to define three breaking intensities leading to three classes of mill products.

The products emerging were analysed either by mechanical sieving or by the sensor system designed for the present study. A 100 g sample was sieved in a Rotex laboratory sifter (Tripette et Renaud, Paris) while the sensor analysis was carried out on-line after the second break roller.

2. The system

The device (schematic diagram shown in Fig. 1) consists of a mechanical system which takes a representative part of the sample. The flow passes through a regulator designed to distribute the product on the whole width of the slot without sorting the particles according to their size. A charge coupled device (CCD) camera synchronized with a strobe (flash duration set by the manufacturer at 20 μs) allows to 'fix' the falling products. Control and data capture are by a PC type computer.

Method and data base

The method chosen consists of comparing a sample to a predetermined quality class. The implementation requires a training phase during which images of samples are captured while the class where they belong is indicated by the operator. This method does not involve any characterization of the classes, as the system finds the most efficient parameters to differentiate them. However the output is not accurate because the composition of the sample is not known, only the predetermined class to whom it is closest is given.

The quality classes can be defined either in relation to the product obtained or as a function of the adjustments of some machine. When buying a product containing various components (such as wheat containing straw) a 'standard product' class can be defined, i.e. a class where the proportions of these components are within acceptable bounds. Classes containing a deficit or an excess of any of the components can consequently be defined. Then, the sensor system will show the deficit or the excess of the selected

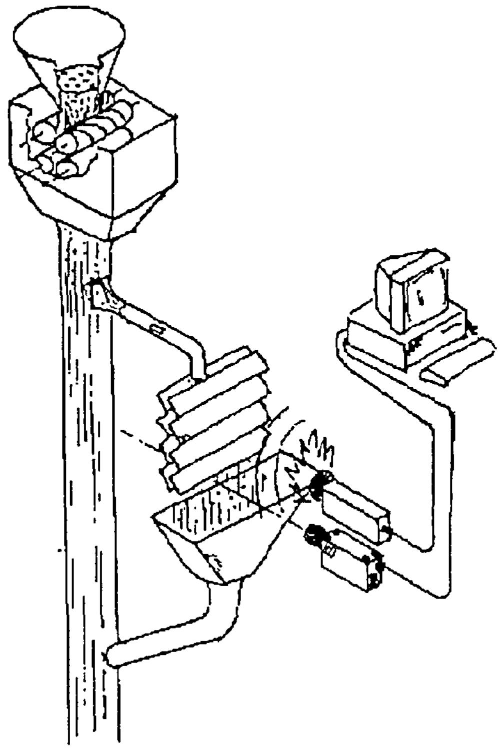

Fig. 1. Diagram of the experimental imaging device.

components. Classes may also be related to machine settings. In this case the system does not deliver any information on the product but rather on the process, thus indicating possible drifts. This option, best suited to the regulation of the processes, was chosen to control mill products.

Three quality classes were defined as a function of the rolls gap of the cylinders: E30, E40 and E50 corresponding to 0·30, 0·40 and 0·50 mm. For each of these classes, 350 images were stored, each containing approximately 130 particles. Figure 2 shows a digital image of mill products. Every sample consisted of 10 images to guarantee a minimal satisfactory representation. Out of 35, 20 samples were used as a training base, i.e. to design the system and 15 to test it.

Data processing

Two kinds of variables can be extracted from a granular products image: individual measurements characterizing each particle as well as global ones related to the whole of the image. In order to handle both types and to avoid losing information, a global representation system was selected which allows an exhaustive assessment of the sample (Ros *et al.*, 1994*a*), i.e. the normalized histogram.

The individual measurements used are: surface and perimeter of the object, aspect ratio, convex hull surface perimeter, object moments (order 1, 2, 3). The aspect ratio is the ratio of the smaller axis of the object to the larger one. It ranges between 0 and 1 (for the circle). It is equal to the ratio of the eigenvalues of the inertia matrix (or covariance matrix):

$$\mathbf{In}=\left\langle \begin{array}{c|c} Sx & Sx,y \\ Sx,y & Sy \end{array} \right\rangle \tag{1}$$

The convex hull of an object is the set defined by the straight lines tangent to the object and including, as shown in Fig. 3.

The centred luminance moments of order p ($p=1,2,3$) are:

$$M^p=\frac{\sum_x [f(x)*(x-m_x)^p]}{[\Sigma f(x)]^p}$$

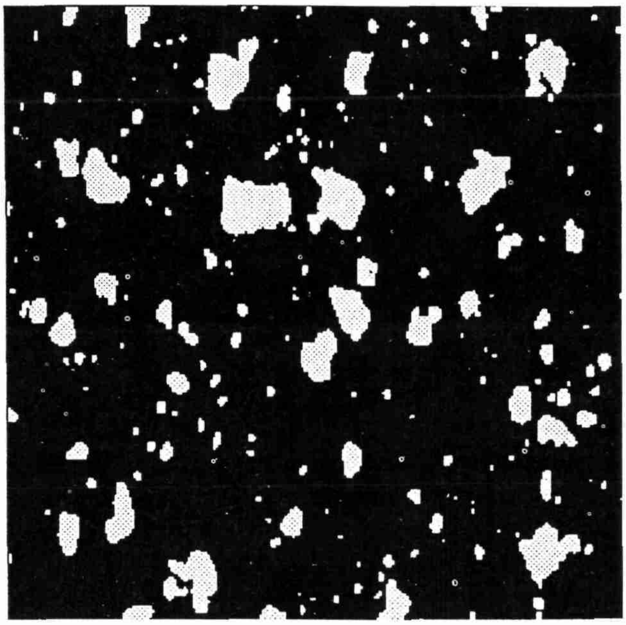

Fig. 2. Digitalized image of mill products.

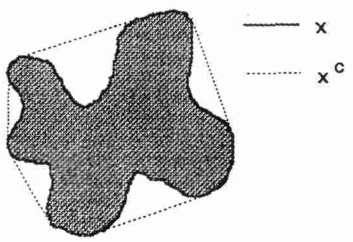

Fig. 3. x^c is the convex hull of x.

They are computed based on the grey level distribution of the object. The distribution is made of 16 intervals of grey level. The limits of the interval number x are $[(x-1)*16; x*16]$. Let $f(x)$ be the number of pixels belonging to interval x and m_x the average interval (empty ones are not taken into account).

The combination of these primary variables leads to dimensionless variables which are independent of the optic system geometry: object surface/convex hull surface, object perimeter/convex hull perimeter, circularity of the object and of its convex hull. The circularity or compactity, is one of the most used shape indexes: it is defined as $(P^2/4*\pi*S)$ where P stands for the perimeter and S for the surface. Its value is 1 for a disc. On the other hand, texture global variables have also been used. Texture is not formally defined, the term being generally understood as the visual or tactile characteristic of a surface. Two techniques, both widely described in the literature (Galloway, 1975), were implemented. The grey levels were grouped into four classes and the class limits were computed dynamically for each image so as to create evenly populated classes. The background (level 0) represents a particular class which is not taken into account in the statistics. As the products were not oriented the scene was analysed in three directions (East, North East, North).

The first of these techniques, the *constant grey level run length*, consists of counting the number of runs of length l and of grey level g in a given direction. For each direction analysed a matrix is obtained. The number of columns is equal to the number of grey level classes (five in this case, i.e. four useful classes and a background) and each row represents a length. Therefore the value C_{gl} represents the number of runs of length l and of grey level g. The parameters proposed in the literature are:

Length level uniformity:

let M_l^r be the moment of the length order r:

$$M_l^r = \frac{\sum_l \sum_g C_{gl} * (l)^r}{\sum_g \sum_l C_{gl}}$$

Let us define $U_{\text{length}} = \frac{M_l^4}{(M_l^2)^2}$

Grey level uniformity:

let M_g^r be the moment if the grey order r, g_m the average grey level of the class:

$$M_g^r = \frac{\sum_g \sum_l C_{gl} * (g_m)^r}{\sum_g \sum_l C_{gl}}$$

Let us define $U_{\text{grey}} = \frac{M_g^4}{(M_g^2)^2}$

Short run indicator:

$$I_c = \frac{\sum_l \sum_g C_{gl}/(l)^2}{\sum_g \sum_l C_{gl}}$$

Long run indicator:

$$I_l = \frac{\sum_l \sum_g C_{gl} * (l)^2}{\sum_g \sum_l C_{gl}}$$

This set of variables added to the ratio I_c/I_l for the three directions is gathered in a variable of size 15.

The normalized histogram was treated as a variable in order to store as much information as possible. It is a vector of size 132. For three directions there are four grey level classes and for each of them 11 length classes (the first 10 containing the number of runs of corresponding length, the eleventh being the total of the runs longer than 10).

In the second technique, *the grey level spatial interdependence*, the number of transitions from one pixel of grey level r to the next one of grey level c are computed in each of the directions analysed in the present application. The distance beween two neighbouring pixels is one. The result is a square matrix, called the co-occurrence matrix, whose size is equal to the number of grey level classes (five in this case). The statistical computations do not take into account the case corresponding to the transitions background–background; C_{rc} represents the number of transactions from class r (row) to class c (column) and g_{rc} the difference between the average grey levels of the row and of the column. From the matrix the maximum of probability can be extraced (max of C_{rc}) and the following terms can be computed:

$$\text{Inertia} = \frac{\Sigma(C_{rc} * (r-c)^2)}{\Sigma C_{rc}} \qquad \text{Heterogeneity} = \frac{\Sigma(C_{rc})^2}{(\Sigma C_{rc})^2}$$

$$\text{Entropy} = \frac{\Sigma(C_{rc} * \text{Ln}(C_{rc}))}{\Sigma C_{rc} * \text{Ln}(\Sigma C_{rc})} \qquad \text{Contrast} = \frac{\Sigma(C_{rc} * (g_{rc})^2)}{\Sigma C_{rc}}$$

As for the constant grey level run length, the variables of the three directions are gathered in a vector of size 15 and to preserve the whole of the information, the co-occurrence matrix is stored in the shape of a variable of size 72, i.e. 24 for each direction. A total of 20 terms were extracted and stored in the shape of a normalized histogram of size 20 for an individual variable and of a size ranging from 15 to 132 for the texture parameters.

The phases of data reduction and selection of information are illustrated in Fig. 4. Every variable is first condensed by factorial analysis (Volle, 1985). Each component of the histogram is treated as a variable contributing to the inertia of the set of data. The factorial analysis changes the initial representation space into a new smaller space where the components are orthogonal to each other (de-correlated) while being linear combinations of the initial variables. Then these components are gathered in a fusion vector. This descriptive method is the first step before the selection method because there is no link between the representativeness of the components in terms of inertia and their potential contribution to the classification. Stepwise discriminant analysis allows the selection of the components which can best help to differentiate the classes. This iterative method maximizes the following ratio:

$$\lambda(r) = \mathrm{DET}(\mathbf{W})/\mathrm{DET}(\mathbf{V})$$

where r is the number of selected independent variables, $\mathbf{V}$ the matrix of variances and $\mathbf{W}$ is the matrix of within-group variances.

The selected variables constitute the input vector of the decision module which consists of two consecutive steps following a hierarchical approach. This procedure is necessary because there may be more than two classes. A one-step system could only be built by satisfying at best the whole set of classes, which would not ensure optimum results for each of them. First step, the generalist system attributes a pertinence coefficient to every possible class as it is not designed to supply the final decision but only to prevent the exclusion from the right class. Second step, the specialist system chooses among the reduced subset of probable classes. This module has been realized thanks to discriminant analysis (Volle, 1985).

RESULTS AND DISCUSSION

The sensor can be characterized both by its intrinsic and its classification performances in the field of experimental milling.

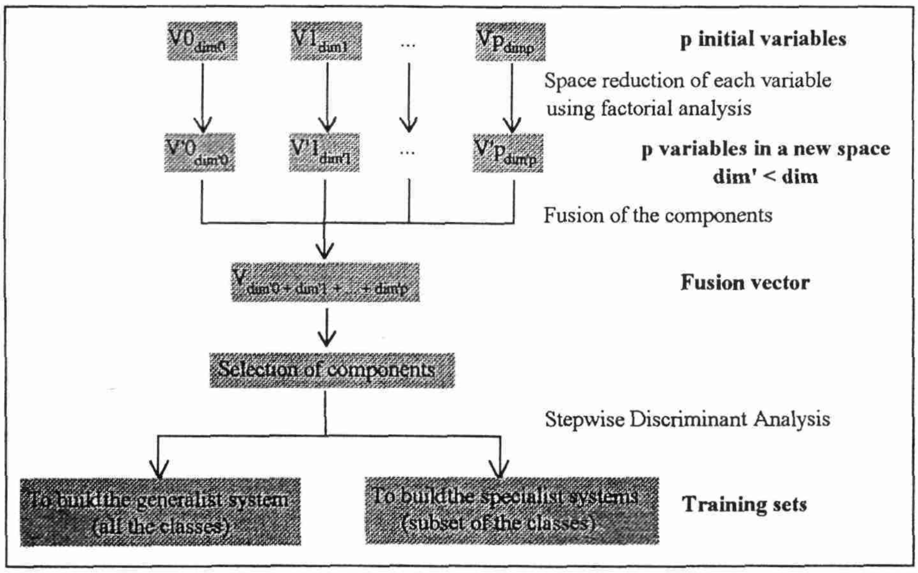

Fig. 4. Data processing schematic diagram.

Intrinsic performances

Measuring range. This depends on the optical geometry chosen. To analyse the output of the first breaker, a 75 mm lens was used. The distance between the lens and the product flow was 1 m. The dimensions of the CCD being $6{\cdot}4 \times 4{\cdot}8$ mm, those of the scene were 85×64 mm. The digital resolution chosen was 256 rows of 256 pixels per run, which means that the width represented by a pixel was 0·33 mm on the horizontal axis and 0·25 mm on the vertical axis. Such a configuration, well adapted to semolina mill products, is not suited for finer products such as flours. In flour milling another optical geometry should be chosen.

Representativeness and resolution (discrimination ability). Since images constitute a sample of the flow it is absolutely necessary to check their representativeness. Usually the assessment of representativeness is done by measuring the cumulative histogram stability. However the main goal of classification is discrimination between the classes even though representativeness (or stability) is implied. Stability and discrimination are not identical notions though they cannot be treated separately. An original measuring method, based on the CHI2 test, was recently designed (Ros *et al.*, 1994*b*). It is a statistical method which computes a suitable number of images to make a representative sample. One of the parameters required for this computation is a success rate for the histogram comparison. This rate was chosen to be 75% and the number of images provided by the method was 10. Should the rate be 85%, 15 images would be needed.

Work frequency. Work frequency is highly dependent on the material and the software used as well as the problem considered. The time required to process an image was estimated at 1 min so the frequency obtained is six decisions per hour. These figures can be improved by optimizing the software (extracting only the most useful characteristics) and by using a more powerful computer.

Classification performances

Let us recall the aim of this study to develop a system capable of characterizing the setting of a breaker (i.e. the roll gap) rather than analysing the composition of some mill product. The performances of this system are therefore correlated to its ability to identify the tightening intensity of the roller mill from which the product is issued. The three classes obtained are close to each other but still quite easy to identify for a craftsman who can assess the different settings of his machines by seeing and touching the mill products. Moreover, a sieve analysis, such as the one illustrated in Fig. 5, is always available. The proportion of fine products increases in relation to the closeness of the rolls. Determining the particle size distribution (Pfost & Headley, 1976) indicates that by intensifying the crushing action the median size (or average equivalent diameter) ranges between 1400 and 1225 μm while the geometrical standard deviation only varies between 598 and 575 μm. It is essential to load the machines as evenly as possible so as to prevent choking as well as variations in the extraction rate and in the purity of the finished products. The curves obtained in Fig. 5 illustrate the influence of the roll gap on the granulometry of mill products. After sieving, the oversize particles are passed onto the next breaker. The sieve aperture of the tailing sifters is 1120 μm. Depending on the chosen roll gap, the percentage of products flowing into the next breaker may vary between 57 and 68%. In the same way, the input of coarse semolinas (size between 450 and 1120 μm) will range from 50 to 67% depending on the tightening of the setting. Such variations in the loading of the purifiers first result in the drift of the partition point between white and brown products, then modify the loading of the head of the scratch rolls which will finally lead to differences in the output and the features of the finished products.

The data provided by the sensor indicate that even though it gives valuable information for the miller, the granulometry does not provide a comprehensive characterization of the samples. The analysis effectively indicates size, and to a lesser extent shape, as the first component (60%), shape proper being the second component (15%), and luminance the third (9%). Moreover, among the parameters taken into account by the model, those related to texture play as important a role as the ones related to individual features.

A data reduction procedure was performed so as to eliminate redundancies. Initially the sample was characterized by 20 parameters, the sum of their dimensions being 554. After principal components analysis of each parameter, the dimension sum was reduced to 75. The whole of these components are gathered in a fusion vector. The selection by stepwise discriminant analysis retains only the most pertinent variables to separate the classes. Generally, the variables selected to build the two steps of the decision system are not the same. The information reduction shows that some image features are not essential and contribute little to the characterization of the sample. For example, as size parameters are highly correlated (more than 90%), only one of them is taken into account.

After this data preparation, a linear separation of the classes appears to be possible (Table 1). Discriminant analysis allows a classification success rate of 81·6% on average: class E30 is very easily separated from the two

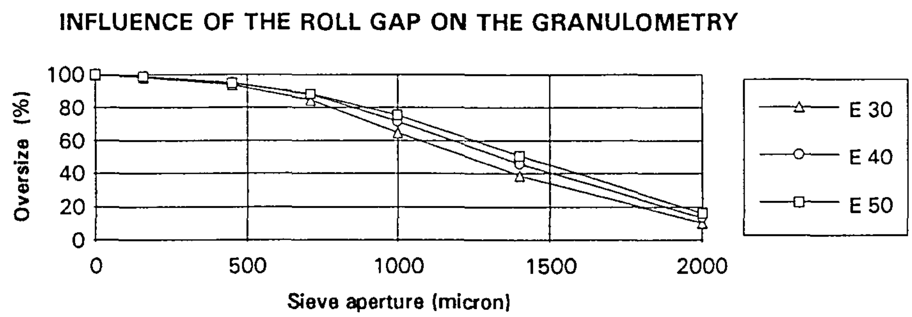

Fig. 5. Size distributions.

TABLE 1
Classification Performances (Discriminant Analysis)

%	*E30*	*E40*	*E50*
Correctly classified	100	81	64
Incorrectly classified	0	19	36

others (100%) while classes E40 and E50 partially overlap. These results highlight the non-linearity of the tightening intensity of the rolls devices. Too tight a gap (E30) logically produces more thin particles, while causing alterations in the mill products (particularly in their shape) that size analysis alone cannot show. In Fig. 5, the differences between two adjoining distributions may not appear clearly while the system isolates class E30, which from the miller's point of view, corresponds to a too intensive breaking.

Though it is virtually impossible to reach a success rate of 100%, these results could be improved by increasing the number of images constituting the sample — 15 instead of 10 — and by increasing the size of the training phase which is reduced to 20 examples here.

These results are encouraging. However they need to be confirmed on a greater number of classes, corresponding to intermediate tightening intensities (0·35 and 0·45 mm, for instance). Moreover, an assessment of the system sensitivity to the features of the wheats to be milled (size, shape, hardness) as well as to the preparation conditions (water content and rest time) should be carried out.

CONCLUSION

Artificial vision appears as a promising technique to characterize and control the granular aspect of mill products. Thanks to the present system images can be taken in-flow, without preparing the sample. Measurements are quick, repeatable and of good accuracy. Variables characterizing isolated particles are taken into account as well as global image variables. The developed methodology allows combination of various variables of different size and nature in order to apprehend the complexity of the product. So, by taking into account other information besides granulometry, the sensor approaches the miller's estimate. Further research, mostly devoted to the improvement of the mechanical device which gathers a portion of the product flow as well as to the system's discriminating ability, is still necessary to achieve devices of real industrial value.

Since granular products are a major problem in a number of food industries (sugar industries, animal food industries...) or other industrial fields (cement works...) this new type of sensor could, in the long run, have many practical applications in a decision making aid in process management.

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