Int J Adv Manuf Technol (2001) 17:751–759

The International Journal of Advanced Manufacturing Technology

Multivalued Fuzzy Sets in Cost/Time Estimation of Flat Plate Processing

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Cost/time estimation in flat plate processing (FPP) is a complex system of man–work–environment–organisation. As the share and impact of physical, psychological, personal, and other characteristics of humans (non-process factors) in this complex system becomes larger, the state of FPP time estimation changes from well-defined to ill-defined (uncertain). In this paper, the effect of process and non-process factors on the activity time variation are discussed and a multivalued fuzzy set (MVFS) is used to model the uncertainty activity time/cost estimation in FPP. Emphasis is placed on modelling of non-random uncertainties using fuzzy sets.

Keywords: Cost/time estimation; Fuzzy sets; Monte Carlo simulation; Probability distributions; Uncertainty

1. Introduction

The flat plate processing (FPP) industry uses high-technology cutting machines with computer numerical control (CNC) and CAD/CAM systems to provide a combination of different processes such as profiling, drilling, and marking in a single machine set-up, for processing sheets and plates in a wide range of dimensions. In an activity-based costing system, these processes are grouped under the heading *activities*. These activities are supported by a range of other activities including drawing and programming, m/c set-up, material carrying and loading, cutting, unloading the cut parts, unloading and returning usable off-cuts, unloading the remaining skeleton, packing the cut parts, loading the packed parts on to a truck, and delivery to the customer. The cost of each activity is the product of a pre-specified activity rate and the corresponding variable activity time. Thus, the key to activity cost estimation is accurate activity time estimation. There are two main groups of variables influencing activity time in FPP, which are classified here as process variables and non-process variables. Process variables such as cutting speed, plate thickness and dimension, which are primary variables, are those directly related to a process or activity. They are well-defined variables whose values are set by the process-planning engineer. Non-process variables such as operator conditions, nature of work, environmental conditions, and management and organisational conditions, on the other hand, are those factors affecting the activity time which cannot be set in advance. They are considered to be the major sources of uncertainty in time/cost estimation in flat plate processing. Therefore, to develop a thorough and comprehensive model, the effects of a large range of different combinations of man–work–environment–management/organisation factors should be taken into account. This complexity leads estimators to oversimplify the problem by the use of conservative assumptions and of averages and approximations resulting in over-estimates or under-estimates. A comprehensive and reliable cost-estimation system, based on detailed cost information for different activities, is becoming an increasingly necessary competitive tool.

2. Background of Uncertainty Treatment in Cost Estimation

The effect and impact of non-process variables on activity-time is normally treated as allowance intervals [1–3]. The majority of techniques used to assess these non-process variables and assign allowances are based primarily on the subjective evaluation and the judgement of the estimator. Allowances are assigned for each factor deterministically using allowance tables to generate an estimate. These estimates are not reliable mainly owing to two types of uncertainty associated with this method. The first one is fuzziness due to imprecise and subjective knowledge about the rate of the effect of these factors and also due to the use of judgmental procedures. The second one is randomness due to the probabilistic nature of some of the non-process factors such as delays and also due to assigning allowances for events which will happen in future but which cannot be predicted and determined precisely and accurately in advance.

Contemporary research techniques in human-centred systems, such as FPP cost/time estimation, are based on the premise that when uncertainty exists an approach to eliminate, rather

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than incorporate, as much of it as possible must be developed, and then whatever uncertainty is left must be explained precisely. Such a premise is a consequence of adapting quantitative methods of analysis directly from physical sciences [4]. According to Zadeh's principle of compatibility [5], at a high level of complexity, precision and significance (of the statements about the system's behaviour) become almost mutually exclusive characteristics. Therefore, an attempt to make precise yet significant statements about the complex relationship between people, machines, and environments and organisation may be an illusive task, and traditional methods have little relevance here.

In an activity-time estimation problem, the assessment and evaluation of activity-time influencing factors using qualitative linguistic terms is quite common and meaningful to estimators. A linguistic variable differs from a numerical variable in that its values are not numbers, but words or sentences in a natural or artificial language. Since words, in general, are less precise than numbers, the concept of linguistic variables serves the purpose of providing a means of approximate characterisation of phenomena which are too complex or too ill-defined to be amenable to description in conventional quantitative terms [6]. In an activity-time estimation model, the values of these linguistic variables may be defined as fuzzy sets. For instance, an operator's skill is a linguistics fuzzy variable and its values are super-skill, excellent, good, average, poor, and so on. Fuzzy set theory makes it possible to consider all uncertainty factors because it does not require a precise mathematical relationship between uncertainty factors and total cost [7–11].

Using ordinary fuzzy sets, it is not always possible to assign precisely a point (numerical value) as the degree of membership in the interval [0,1] to each element of a fuzzy variable (estimator's perception) without loss of at least some part of the information. Furthermore, the output result of a model based on ordinary fuzzy sets is a crisp value, i.e. a point estimate, which is not reliable for an uncertain situation. To overcome these drawbacks, this paper describes the application of multivalued fuzzy sets (MVFS) for developing a model for time/cost estimation in FPP considering the uncertainty due to non-process factors. The effects of process and non-process factors on the activity time variation are discussed in detail. The model is illustrated with an example from FPP and analysed using the Monte Carlo simulation technique.

3. Effect of Process Variables on Activity-Time Variation

To investigate the pattern of the activity-time variation, a time study was conducted for a set of activities in FPP. As an example, the result of time study of the plate carrying and loading activity is shown in Figs 1 and 2, demonstrating a great deal of variability. In order to understand and control this pattern, it is necessary to investigate the cause(s) for this wide range of activity time variation. Plate size (PS) is a primary process variable in the plate carrying and loading activity in FPP. As the size of a plate increases, the number of clamps necessary to hold the plate increases, crane speed decreases, and positioning time increases accordingly. Thus,

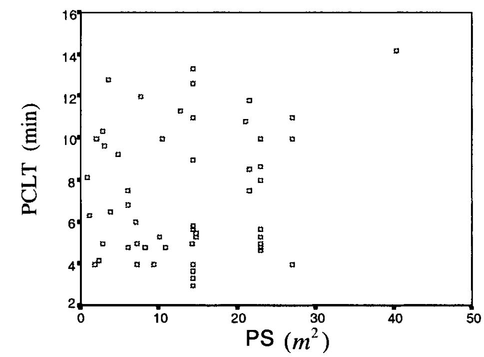

Fig. 1. Plate size (PS) versus plate carrying and loading time (PCLT).

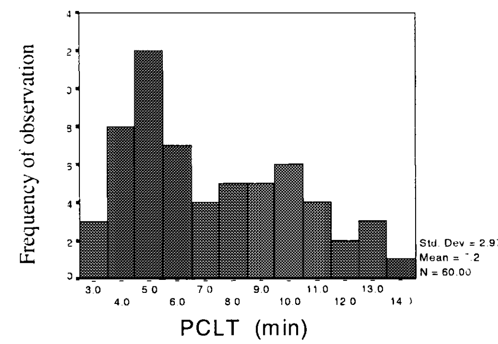

Fig. 2. Histogram of PCLT.

plate carrying and loading time (PCLT) must increase as PS increases. However, as can be seen from Fig. 1, eight different plate sizes ranging from 2 to 28 m^2 have all taken 4 min to be carried and loaded.

Another interesting point is that carrying the same plate size, i.e. 15 m^2, has taken different times ranging from 3 to 13 min in different trials. Further analysis of the collected data consisting of 60 observations, as shown in Fig. 2, reveals that average PCLT time is $\overline{T}_{PCL} = 7.2$ with a standard deviation $\sigma_{PCL} = 2.97$. The correlation coefficient between PS as the independent variable and PCLT as the dependent variable is $r = 0.2$, and the coefficient of determination, $r^2 = 0.04$. This implies that the proportion of the total variation of the dependent variable PCLT that can be accounted for or explained by a linear relationship with the values of independent variable PS is 4%. The pattern of PCLT variation, as depicted in Fig. 1, does not suggest any type of specific nonlinear relationship between PCLT and PS. Therefore, the activity-time estimation cannot be modelled and solved accurately and reliably by considering only process variables. Thus, the question is raised: what factors are responsible for these PCLT variations? It is suggested that, in addition to the process variables, there exist some other factors including non-process variables, which strongly influence activity-time.

4. Effect of Non-Process Variables on Activity-Time Variation

In a CNC environment with high-precision machining, it is reasonable to assume that variations of process factors are so predictable that it puts them into a deterministic category. Therefore, it suffices to concentrate more on non-process factors as the main source of variability. As mentioned in Section 1 and illustrated in Fig. 3, each of these four main categories of non-process variables can be further broken down into several activity-time influencing elements. In the following section, the influence of each of these elements on activity time will be discussed.

4.1 Operator Conditions

Differences in output of different operators working under identical conditions can be attributed to skill and effort. Skill is defined as "proficiency at following a given method", and effort is defined as "demonstration of the will to work effectively". In other words, effort is representative of the speed with which skill is applied and can be controlled to a high degree by the operator [12].

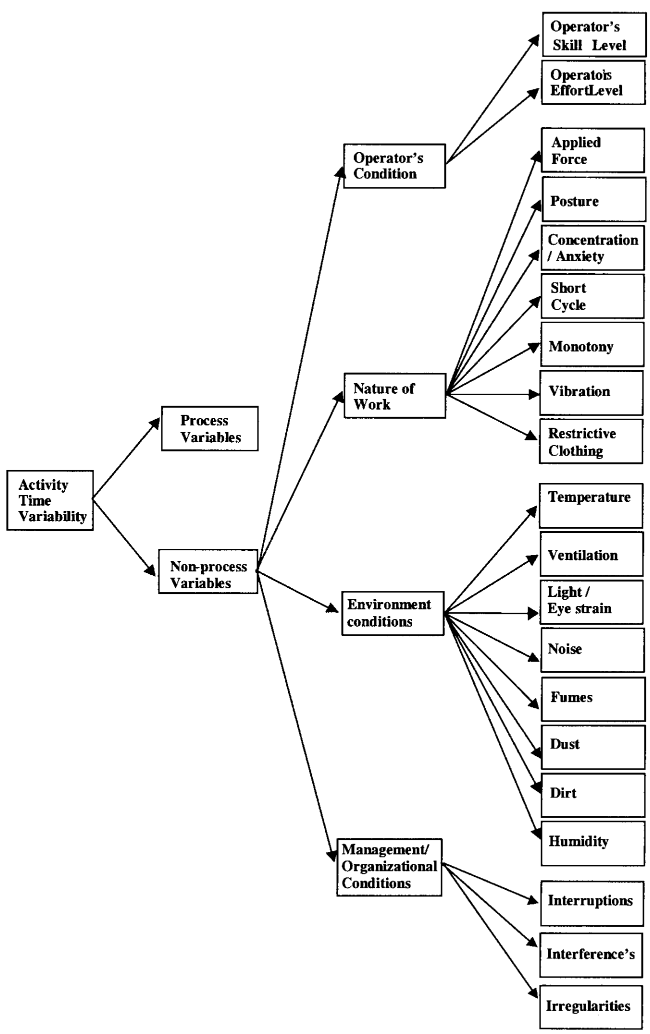

Fig. 3. Factors influencing activity-time variability.

4.2 Nature of Work

The effect of the nature of work on activity-time can be explained by the amount of stress imposed on the operator while performing that activity. This stress causes strain and fatigue in the operator, which, in turn, affects the performance rate. Those aspects of the work which cause fatigue in the operator can be listed as applied force, posture, concentration/anxiety, short-cycle repetitive work elements, monotony, vibration, and restrictive clothing. Whether fatigue is physical or psychological, the result is the same: "there is lessening in the will to work" [3].

4.3 Environmental Conditions

The environmental and atmospheric conditions including temperature, humidity, light, noise, ventilation, fumes, dust, and dirt have a significant impact on an operator's performance [2,13,14]. Under extremes of hot and/or humid environments, blood flow to the skin increases to dissipate the body heat. This reduces the blood flow (venous return) to the heart, and therefore, cardiac output per beat decreases. These conditions may lead to muscle fatigue, leg swelling, abdominal upsets (nausea), loss of consciousness, severe headache, visual disturbance, fainting, giddiness, and possible cardiac failure. Good visibility of the equipment, the product and data involved in the work process is an essential factor in accelerating production, reducing the number of defective objects, cutting down waste and preventing visual fatigue and headaches among the workers. All types of noise including constant, intermittent, or loud and pitched sounds tend to excite workers emotionally and are conducive to worker fatigue, resulting in loss of temper and difficulty in doing a precision job. The nature and concentration of fumes can be injurious to health by irritating eyes, nose, throat, and skin or they can be toxic or have a disagreeable odour and can cause mental fatigue. Since the cubic volume of working premises can never be large enough to make ventilation unnecessary, ventilation should be looked upon as another important factor in maintaining the worker's health and productivity.

4.4 Management and Organisational Conditions

The other major reasons for the occurrence of delays in FPP are interruptions, machine interference, and material and equipment irregularities. Interruption delays can be due to a wide range of reasons such as supervisors giving instructions or clarifying written information, inspectors pointing out the reasons for defective work, or by fellow workers, planners, expediters, and others. Material irregularity delays can also be due to a wide range of reasons such as material being in the wrong location, or the process running too slowly or too quickly, or excessive stock, equipment breakdown, and so forth. Machine interference delays are mainly due to assigning more than one machine to an operator. Although these delays cannot be eliminated, they can be reduced drastically by providing an well-organised and engineering-minded production management system.

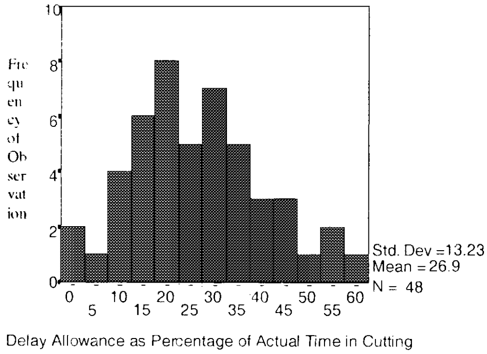

Fig. 4. Histogram of cutting machine stoppage time due to delays.

The time study for the cutting activity illustrated in Fig. 4 shows that a 95% confidence interval of cutting machine stoppage time in the cutting activity is [0.44, 53.36]. Based on these results, up to an 18% stoppage or delay allowance has been used for each of these main factors which are listed in Table 1. Many factors can be considered as grounds for these delays, but the main factors responsible are interruptions, interference, and irregularities [3]. Although these factors seem to be random by nature, they can, to some extent, be controlled and reduced under a well-developed production management system and engineering minded organisation.

Table 1. Allowances for activity–time influencing factors.

Major variable classes	Activity time variables	Allowances
		Performance allowance:
Operator conditions	1. Skill level	[–15,22]
	2. Effort level	[–13,17]
		Relaxation allowance:
	3. Use of force	[0,130]
	4. Posture	[0,16]
	5. Short cycle	[0–10]
Nature of work	6. Concentration	[0–16]
	7. Monotony	[0–10]
	8. Vibration	[0–15]
	9. Restrictive clothing	[0,20]
		Relaxation allowance:
	10. Temperature	[0,18]
	11. Noise	[0,10]
	12. Light	[0,10]
Environmental conditions	13. Ventilation	[0,15]
	14. Fume	[0,12]
	15. Dust	[0,12]
	16. Dirt	[0,10]
	17. Humidity	[0,18]
		Delay allowance:
Management organisation conditions	18. Interruptions	[0,18]
	19. Interferences	[0,18]
	20. Irregularities	[0,18]

5. Effects of Non-Process Variables as Allowance Figures

Consideration of Sections 4.1 to 4.4 leads to the identification and characterisation of 20 different activity-time influencing factors, as illustrated in Fig. 3. Because so many inter-related factors are involved in activity time, it is too complicated, time-consuming, and expensive to model these factors in a universally accepted activity-time/cost estimation system using mathematical or even analytical–experimental approaches. For instance, many attempts such as physical, chemical, and psychological tests have been made to measure fatigue, none of which have been completely successful [14]. Current practice considers these influences as different allowances including performance allowance, fatigue allowance, and delay allowance [1], as illustrated in Table 1. The allowances as percentage of normal activity time are added to the normal time. Empirically established allowances are set out as tables, and have been satisfactory for work involving normal or moderately intensive effort [15–17].

As these factors exist in a real manufacturing cycle, ignoring them will result in distorted and inaccurate estimates. For example, the activity time will be increased by non-process variables including force, temperature, and humidity, under pessimistic conditions, up to 130%, 18%, and 18% of normal activity time, respectively. As another example, if a super-skilled operator working very hard is employed, the activity time will be reduced by up to 28%, but if a very poor operator is employed, the activity time will be increased by up to 39%. The total accumulated variation of activity time caused by only these five factors (force, temperature, humidity, operator skill, and operator effort) out of the twenty major factors, is [–28, 205], i.e. up to 28% less than normal time in an optimistic condition, and up to 205% more than normal time in a pessimistic condition. Activity total time, T_{ti}, for the ith activity, $i = 1,2,3,\ldots,n$, in performing a job order can be represented as:

$$T_{ti} = T_n \left(1 + \frac{AT_b + \sum_{j=1}^{m} AT_{ij}}{100} \right) \tag{1}$$

Where T_n is activity normal time, AT_b is fixed basic allowance time including personal allowance and basic fatigue allowance, AT_{ij} is variable allowance time caused by non-process variables (uncertain factors) for each activity, and, $i,j = 1,2,3,\ldots,m$ denotes different non-process uncertainty factors. Activity normal time can be determined by using only process variables. The key issue is how to deal with the variable allowance, AT_{ij} in Eq. (1). As mentioned in Section 2, AT_{ij} has been treated deterministically, and is a combination of twenty different uncertain factors (non-process variables). There are two types of uncertainty to be considered. The first one is fuzziness due to imprecise and subjective knowledge about the rate of effect of these factors, and also due to use of judgemental procedures. The second one is randomness due to the probabilistic nature of some of the non-process factors such as delays, and also due to assigning allowances for events which will happen in the future but which cannot be predicted precisely and accurately.

Table 2. Cost of different activities in FFP.

		MVFS output results			
		CCR	ORG	DCI	FD
Different activities in FPP					
DP	OP	38.59	39.26	40.6	
	ML	40.59	42.6	43.09	43.4
	PE	45.2	47.53	48.7	
Set-up	OP	285.95	296.91	313.14	
	ML	327.79	350.76	362.75	369.71
	PE	395.28	429.05	458.84	
PCL	OP	47.3	48.56	50.95	
	ML	55.79	60.49	63.59	66.69
	PE	72.78	78.97	86.28	
Cutting	OP	2998.35	3192.81	3251.09	
	ML	3088.08	3307.97	3375.5	3631.22
	PE	3782.34	4004.02	4313.92	
UCP	OP	132.22	136.25	141.82	
	ML	154.91	166.37	173.13	189.2
	PE	192.63	208.32	228.49	
USK	OP	119	122.62	127.64	
	ML	139.42	149.73	155.82	162.01
	PE	173.37	187.48	205.64	
Packing	OP	17.19	17.71	18.44	
	ML	20.14	21.63	22.51	23.47
	PE	25.04	27.08	29.7	
LCP	OP	132.33	135.72	140.45	
	ML	150.09	159.76	164.56	172.62
	PE	182.83	197.06	213.18	

Therefore, a hybrid system of probability and fuzzy set theory can be used as a promising tool for modelling of cost/time estimation.

6. Ordinary Fuzzy Sets

A fuzzy set, which is a set of objects without clear or sharp boundaries, is especially useful for the representation of imprecise knowledge [18]. A fuzzy set can be seen as predicates whose truth values are drawn from unit interval, $I = [0,1]$ rather than the set of $\{0,1\}$ as in the case of an ordinary set. By definition, a fuzzy set, A, defined on a universe of discourse, X, (the domain of fuzzy variable) is characterised by a membership function, which takes on values in the closed interval, I. Formally, a fuzzy set can be represented as follows:

$$A = \{(x,\mu_A(x)) \mid x \in X,\ \mu_A(x) \in [0,1]\} \tag{2}$$

As explained earlier, input values (non-process variables) of the fuzzy model cannot be measured objectively or assigned precisely. They are assigned through subjective evaluation and judgement of the estimator using allowance tables. There is a possibility of an over-estimate, $x_{o,c}$, or an under-estimate, $x_{u,c}$, as shown in Fig. 5. The membership function of ordinary fuzzy

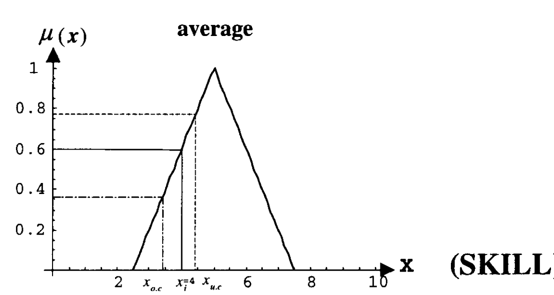

Fig. 5. Membership function of ordinary fuzzy set for average in fuzzy variable SKILL.

sets assign precisely a point (numerical value) as a membership value $\mu_A(x_i)$ in the interval [0,1] to each element of fuzzy variable $x \in X$ (estimator's perception). The mechanics underlying ordinary fuzzy sets cannot solve the problem of over/under estimation so at least some part of the information will be lost. Another limitation of ordinary fuzzy sets is that they generate crisp outputs, which are not reliable in the presence of uncertainty. This problem can be overcome by using multi-valued fuzzy sets.

7. Multi-valued Fuzzy Sets (MVFS)

If fuzzy sets are designed in such a way that for each element, x_i, of the universal set, e.g. operator's skill X, an interval of membership grade could be provided, then the uncertainty would be captured and reduced to an interval. Thus, to deal with this problem, a reasonable way is to include this uncertainty in the definition of the membership functions of the fuzzy variable by modifying them through identifying the original (ORG), concentration-contrast relaxation (CCR) and dilution-contrast intensification (DCI) membership function, as illustrated in Fig. 6. A membership function defined on the basis of this concept does not assign only one real number as a membership value to each element of its universal set, but a closed interval of real numbers obtained from the identified upper and lower bound membership functions. Therefore, the problem of generating a crisp output as a point estimate, discussed in Section 6 and shown in Fig. 5, can be solved. There are different procedures for designing these types of membership functions. One is using hedges to intensify and dilute the region of a fuzzy set [19–21]. Hedges play the same role in a fuzzy modelling system as adverbs and adjectives do in English. They modify the nature of a fuzzy set. Zadeh's original definitions for concentrator hedge "very" and dilutor hedge "somewhat" are squaring and taking the square root of the base membership function, respectively [21]. There is no justification for representing hedges in this way and the conventions used in the literature are, in general, subjective. Therefore, the hedges can be defined in different shapes and formats. The triangular ORG membership function of the fuzzy set average of the fuzzy variable SKILL can be written as:

$$\mu_{\mathrm{ORG}}(x) = \begin{cases} 0 & \text{for} \quad x \le a \\ \dfrac{x-a}{b-a} & \text{for} \quad a < x \le b \\ \dfrac{d-x}{d-b} & \text{for} \quad b < x \le d \\ 0 & \text{for} \quad d \le x \end{cases} \tag{3}$$

The CCR membership function which is defined through the concentration and contrast-relaxation of the ORG membership function, can be written as:

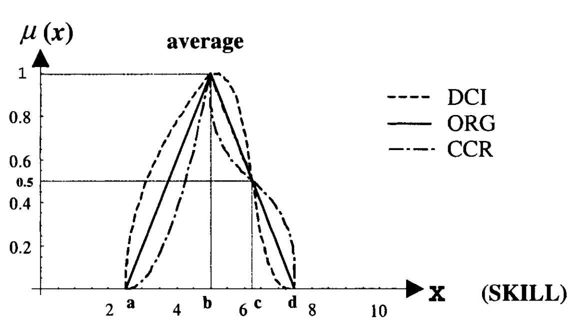

Fig. 6. Membership function of MVFS for average in fuzzy variable SKILL.

$$\mu_{\mathrm{CCR}}(x) = \begin{cases} 0 & \text{for} \quad x \le a \\ \left(\dfrac{x-a}{b-a}\right)^{3} & \text{for} \quad a < x \le b \\ 1 - 0.5946\left(1 - \dfrac{d-x}{d-b}\right)^{0.25} & \text{for} \quad b < x \le c \\ 0.5946\left(\dfrac{x-a}{b-a}\right)^{0.25} & \text{for} \quad c < x \le d \\ 0 & \text{for} \quad d < x \end{cases} \tag{4}$$

The DCI membership function which is defined through the dilution and contrast-intensification of the ORG membership function, can be written as:

$$\mu_{\mathrm{DCI}}(x) = \begin{cases} 0 & \text{for} \quad x \le a \\ \left(\dfrac{x-a}{b-a}\right)^{0.33} & \text{for} \quad a < x \le b \\ 1 - 8\left(1 - \dfrac{d-x}{d-b}\right)^{4} & \text{for} \quad b < x \le c \\ 8\left(\dfrac{x-a}{b-a}\right)^{4} & \text{for} \quad c < x \le d \\ 0 & \text{for} \quad d < x \end{cases} \tag{5}$$

8. MVFS Algorithm

The twenty non-process variables mentioned in Section 3, are used as inputs to the MVFS model to generate the output showing the total allowance time for each activity in the FPP. The optimistic (OP), most likely (ML), and pessimistic (PE) concepts are considered in the MVFS model for inputs under the optimistic, most likely, and pessimistic conditions. The procedure for calculating the output of the proposed rule-based MVFS model, which is illustrated in Fig. 7 as a block diagram, is based on the following ten steps:

1. Fuzzify the twenty different input variables for the ML condition.
2. Make the inference, which consists of two processes: fuzzy implication and rule aggregation. The Mamdani method is used for inferring the rule output [6].
3. Carry out defuzzification, which generates three crisp outputs from ORG, CCR, and DCI fuzzy sets obtained from aggregation process for each input variable. The centre of area method [19] is used for defuzzification.
4. Calculate total ORG, CCR, and DCI allowance time under ML condition:

$$ORG_{ML} = \sum_{j=1}^{20} ORG_j \tag{6}$$

$$CCR_{ML} = \sum_{j=1}^{20} CCR_j \tag{7}$$

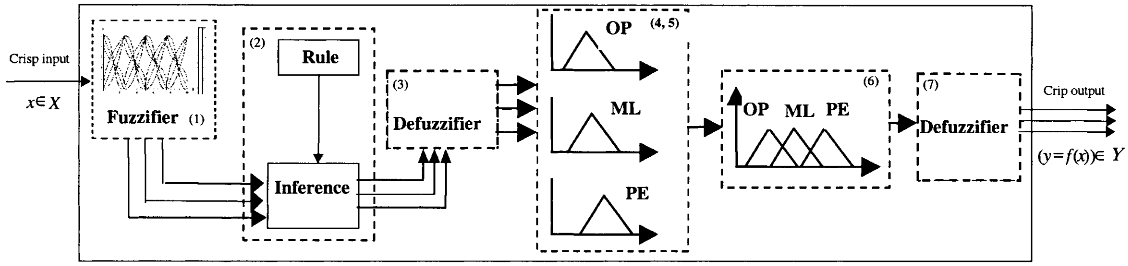

Fig. 7. A block diagram of the MFVS. OP, optimistic; ML, most likely; PE, pessimistic.

$$DCI_{ML} = \sum_{j=1}^{20} DCI_j \tag{8}$$

5. Calculate total ORG, CCR, and DCI activity time under ML condition using Eq. (1).
6. Repeat steps 1 to 5 twice more to generate allowance time estimates under OP and PE operator–work–environment–organisation conditions in a similar way. Up to this stage, nine different estimates of activity time including ORG_{ML}, CCR_{ML}, DCI_{ML}, ORG_{OP}, CCR_{OP}, DCI_{OP}, ORG_{PE}, CCR_{PE}, DCI_{PE} are generated. Thus, the interval estimate of activity time can be presented as: $[CCR_{OP}, DCI_{PE}]$.
7. Define three new triangular fuzzy sets for ML, OP, and PE input variable conditions based on the corresponding nine different estimates of step 6.
8. Aggregate the three newly defined triangular fuzzy sets of step 7.
9. Defuzzify (DF) the aggregated fuzzy set of step 8 to provide the most possible activity time.
10. Calculate the cost of each activity based on the corresponding estimated activity time using the following relationship:

$$C_i = R_i \times T_{ti} \tag{9}$$

Where R_i and T_{ti} are the rate ($/h) and total time of ith activity, respectively.

The output of this fuzzy model will be an interval estimate of activity cost, which contains the point estimate of the most possible activity cost, based on probabilistically assigned fuzzy information. The MVFS model is repeated for all activities necessary to complete a job order in FPP. The uncertainties of each activity cost/time are captured and reduced into an interval. The analysis of the output results and its representation in a more understandable form is the subject of the next section.

9. Uncertainty Analysis Using the Monte Carlo Simulation Technique

To this point, the uncertainties in activity cost estimation in FPP have been captured and reduced to an interval. This estimate consists of the minimum or lower bound of optimistic (CCR_{OP}), most likely, or final defuzzification (*DF*) of the MVFS model, and the maximum or upper bound of the pessimistic activity costs (DCI_{PE}). These three estimates, reflecting the inherent uncertainties, are converted into a triangular probability distribution. To combine and analyse uncertainties, the Monte Carlo simulation technique [22], is used to generate each activity cost, based on the corresponding triangular probability distribution. A flowchart of the uncertainty analysis procedure is illustrated in Fig. 8. The total cost of the order is equal to the algebraic sum of the cost of the activities of the critical path in the sequence network of activities as:

$$C_t = \sum_{i=1}^{n} C_i \tag{10}$$

10. Experimentation

Suppose an FPP company receives an order from a customer to cut 100 pieces of the shape shown in Fig. 9 from a mild steel plate of 20 mm thickness. The customer requested a maximum of 4 finished parts in each bundle. The engineering department provides the following information: total cutting length for each part is 10 982 mm, cutting speed is 1700 mm min^{-1}, plate dimension is 9000×3000 mm^2, and time-values of the plasma cutting machine, material handling machines, and computer (software–hardware) cost 100, 15,

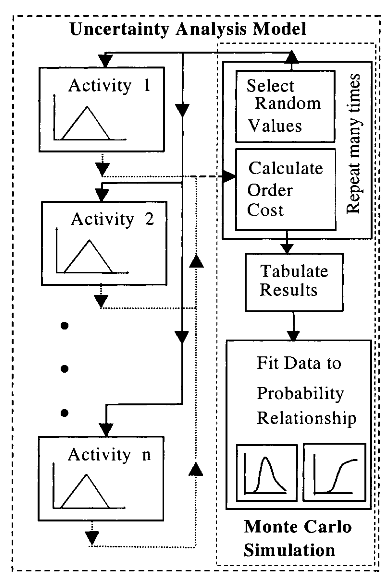

Fig. 8. Flowchart of uncertainty analysis procedure.

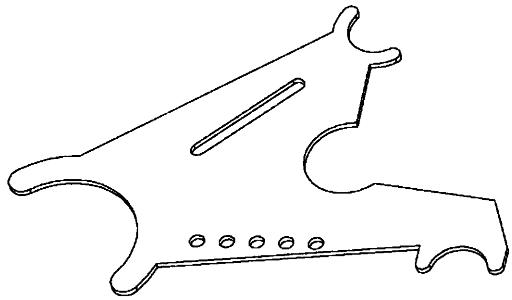

Fig. 9. The order to be cut from steel plate.

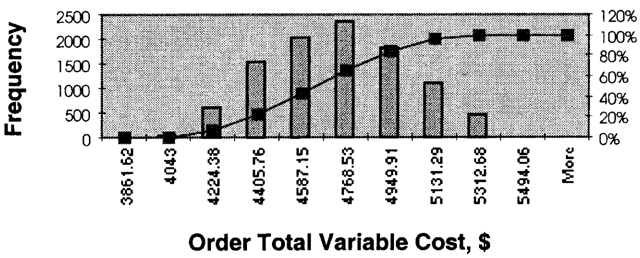

Fig. 10. Cumulative probabilities of order cost.

15 $ h^{-1}, respectively. The output results of the MVFS model are shown in Table 2. The abbreviations DP, PCL, UCP, USK and LCP in Table 2 stand for drawing/programming, plate carrying/loading, unloading cut parts, unloading skeleton and loading cut parts for delivery, respectively.

Figure 10 shows the result of the Monte Carlo simulation. The total cost of the order is represented by a probability distribution indicating the estimated range of costs and the likelihood of costs within the range. As illustrated in Table 2 and Fig. 10, point and interval estimates of the cost/time for each activity and also for the job order are provided. This methodology provides traceable cost/time estimates by generating cost/time estimates for all individual activities in FPP. The uncertainty analysis process can be used to provide more detailed information and different useful measures of cost/time for each activity, which are necessary and essential for decision-making on quotation, process selection, productivity improvement, and so on. For example, if the customer is not a one-off and is a very important one or the manufacturing market is very competitive, then optimistic cost (lower cost) should be considered for producing quotes, otherwise pessimistic cost (higher cost) should be considered.

11. Conclusion

In flat plate processing the activity-time variation is attributed to process and non-process variables. Process variables such as cutting speed, plate thickness, plate dimension, crane speed, and so on are deterministic and predictable with certainty. On the other hand, non-process variables characterised by four main categories of time-influencing factors, namely, operator, nature of work, environmental, and organisation, are not deterministic and cannot be predicted with certainty. The time study carried out indicates that only a minor section of variation in activity time can be captured and explained by process variables, whereas non-process factors are responsible for a major section of this variation. Therefore, uncertainty is a significant feature in FPP time/cost estimation. A model using a new configuration of fuzzy sets called multivalued fuzzy sets (MVFS) was developed to capture these uncertainties and reduce them to an interval containing optimistic, most likely, and pessimistic activity-time estimates. Then, these uncertainties are analysed by defining triangular probability distributions for each activity and using the Monte Carlo simulation technique. Using this methodology, different qualified values of order cost/time in FPP in the form of confidence intervals and the chances of the final cost being less than a particular value are provided. The developed model can be adapted and matched to different operator–work–environment–organisation conditions by recalibrating the model simply and quickly through shifting its membership functions to provide more flexibility for cost/time estimators.

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