Analysis and research on the simulation and output of discrete event system with fuzzy parameters

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Abstract

This paper discusses discrete event system simulation output analysis method with fuzzy input parameter. For a classic discrete event model, which contains randomness, once stimulation running is only a sampling according to systematic behaviour, which could not represent all features of the system. Hence, there should be a systematic analysis method, under the guidance of which to apply multi-times stimulation of model and analyse output data of stimulation. This paper provides a solution and introduces random fuzzy theory at last to improve traditional output analysis method. Result of stimulation experiment proves that the method could improve the reliability of stimulation output analysis.

Keywords: Discrete event system, Fuzzy Parameters

1 Introduction

This paper mainly contains two sections: single system output analysis method based on fuzzy discrete event stimulation and evaluation of influence of input parameter fuzziness on stimulation output result.

Section One analyses problems of stimulation output analysis method in discrete event system with fuzzy parameters, provides solutions and improves traditional output analysis method by introducing random fuzzy theory at last. Result of stimulation experiment proves that the method could improve reliability of stimulation output analysis.

Section Two provides influence index of evaluating fuzziness of input parameter on stimulation output, including absolute index and relative index. Absolute index could perform single evaluation of influence of some input parameter on stimulation output and relative index could compare the influence of each parameter on output. At last application of the method is illustrated through stimulation experiment.

2 Numerical characteristics of random fuzzy variable

Among computer algorithm, it always requires numerical characteristics such as mathematical expectation or variance of some random fuzzy variable. For random variable, it could sample in probability space, use method of statistical to evaluate corresponding numerical characteristics [1]. However, because law of large numbers does not exist in possible space, method of statistical could not be used to evaluate mathematical expectation or variance of some random fuzzy variable. Hence, corresponding computer stimulation algorithm should be designed based on definition of each numerical characteristic [2, 3].

Method 1: Calculate expectation of random fuzzy variable ξ in possible space (Θ , P(Θ), Pos).

1) Select N $\theta_k(k=1,2,\ldots,N)$, which satisfy $Pos\{\theta_k\}\succ 0$ from Θ;

2) Make $i=1$;

3) Evaluate expectation $E[\xi(\theta_t)]$ of random variable $\xi(\theta_i)$;

4) If i<N, then i=i+1, return 3);

5) Make, $b=\max_{1\le i\le N} E[\xi(\theta_i)]$;

6) Randomly generate M number $r_k(k=1,2,\ldots,M)$ from section $[a,b]$;

7) Make sum=0, j=1;

8) If $r_j\ge 0$, then $sum=sum+Cr\{\theta\in\Theta | E[\xi(\theta)]\ge r_j\}$, or $sum=sum-Cr\{\theta\in\Theta | E[\xi(\theta)]\ge r_j\}$;

9) If j<M, then j=j+1, return 8);

10) Calculate $E[\xi]=a\vee 0+b\wedge 0+sum(b-a)/M$.

Algorithm to calculate variance is to calculate expectation of ξ^2 and ξ separately, then calculate $V[\xi]$.

Method 2: Calculate variance of random fuzzy variable ξ .

1) Use method 1 to calculate $E[\xi^2]$ of random fuzzy variable ξ^2;

2) Use method 1 to calculate $E[\xi]$ of random fuzzy variable ξ;

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3) Calculate $V[\xi]=E[\xi^2]-(E[\xi])^2$.

3 Stimulation data analysis of fuzzy discrete event

3.1 INFLUENCE OF INPUTTING INCORRECT PARAMETER ON STIMULATION OUTPUT ANALYSIS

In order to explain the influence of inputting incorrect parameter on stimulation output analysis, next experiment is designed to illustrate this issue.

Let's consider an M/G/1queue model, in which process of customer coming is a simple Poisson process, process parameter $\lambda = 1/15$ service table is independent identically distribution for each customer service, mean value is p time unit, variance is 1; performance index which users care is average waiting time W_q of each customer as system is stable.

Now, suppose that true value of p is 10, but stimulation modelling analyst does not know this value; and suppose that it is not allowed to take samples of service time in large quantities to evaluate value of p. There could only be 5 samples at most and mean value of 5 samples is value of pin the model.

Next, use true value p=10 and sampling evaluation value as input parameter separately to run 100 times independent stimulation and calculate confidence interval with confidence level of 90% [4, 5]:

$$\overline{W_q}(n) \pm t_{n-1,1-\alpha/2}\sqrt{\frac{S_n^2(W_q)}{n}}$$
$$\overline{W_q}(100) \pm 0.166\sqrt{S_{100}^2(W_q)} \quad . \quad (1)$$
$$\overline{W_q}(100) \pm t_{99,0.95}\sqrt{\frac{S_{100}^2(W_q)}{100}}$$

Then verify if this interval contains true value of W_q:

$$W_q = \frac{\lambda(1-\mu^2\sigma_S^2)}{2\mu(\mu-\lambda)} = \frac{\frac{1}{15}\left(1-\frac{1}{10^2}\right)}{\frac{2}{10}\left(\frac{1}{10}-\frac{1}{15}\right)} = 9.9 . \quad (2)$$

In order to verify if confidence interval built could reach confidence level of 90% which is required, 100 times independent experiments are applied for both conditions separately. Statistical stimulation result is "correct", i.e. confidence interval contains times and proportion of true value of 9.9. Experiment result is illustrated in table 1.

It can be told, that using inaccurate information to build system model causes severe deterioration of result of classic stimulation output analysis. And it lowers meaning of system stimulation. Hence, if model input parameter is inaccurate, it must be handled to improve method of stimulation output analysis and keep the result of stimulation reliable.

TABLE 1 Comparison of 90% confidence interval built by using accurate parameter and inaccurate parameter

Experiment order	**Using accurate parameter**		**Using inaccurate parameter**		
	Confidence interval	*Contains true value*	*Parameter P value*	*Confidence interval*	*Contains true value*
1	[9.6161,10.090]	Y	9.4337	[7.6949,8.1134]	N
2	[9.5746,10.146]	Y	10.569	[12.093,12.889]	N
3	[9.7620,10.291]	Y	10.400	[11.284,12.007]	N
4	[9.8680,10.339]	Y	10.062	[9.8531,10.451]	Y
5	[9.7634,10.209]	Y	10.121	[10.086,10.703]	N
6	[9.7908,10.282]	Y	9.9297	[9.3474,9.9017]	Y
7	[9.8805,10.408]	Y	10.622	[12.359,13.179]	N
8	[10.038,10.598]	N	10.096	[9.9864,10.595]	N
9	[9.7846,10.341]	Y	9.6414	[8.3448,8.8155]	N
10	[9.7657,10.274]	Y	9.5193	[7.9559,8.3952]	N
11	[9.7177,10.272]	Y	10.479	[11.656,12.412]	N
12	[9.7611,10.225]	Y	9.7320	[8.6466,9.1421]	N
……	……	……	……	……	……
96	[9.7648,10.309]	Y	9.8510	[9.0611,9.5912]	N
97	[9.9056,10.444]	N	9.3565	[7.4674,7.8681]	N
98	[9.7687,10.290]	Y	9.2652	[7.2071,7.5876]	N
99	[9.8506,10.306]	Y	9.7417	[8.6796,9.1779]	N
100	[9.6661,10.201]	Y	9.7611	[8.7460,9.2498]	N
Correct times (proportion)			89(89%) 12(12%)		

3.2 TWO METHODS OF SOLVING DETERIORATION OF OUTPUT ANALYSIS RESULT

Aim of supposed stimulation is to evaluate expectation $E[y]$ of some output variable y, then run n times independent stimulation, using sampling mean value $\bar{y}(n)$ to evaluate $E[y]$ and build confidence interval of confidence level $(1-\alpha)$ as follow [6]:

$$\bar{y}(n) \pm t_{n-1,1-\alpha/2}\sqrt{\frac{S_n^2(y)}{n}} . \quad (3)$$

According to central-limit theorem, several mean values of random variables of IID are similar to normal distribution. Hence, distribution of $\bar{y}(n)$ could be recognized as normal distribution and use $E[y]$ as expectation. When input parameter of system model is inaccurate, expectation of $\bar{y}(n)$ could deviate from $E[y]$. See figure1.

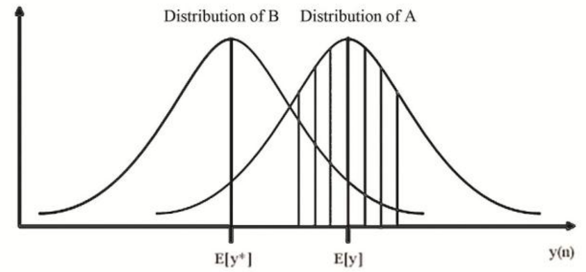

FIGURE 1 Probability density function of $\bar{y}(n)$

Among those, distribution A is probability distribution of $\bar{y}(n)$ when input parameter is accurate. If $\bar{y}(n)$ is in section of $E[y]\pm t_{n-1,1-\alpha/2}\sqrt{\frac{S_n^2(y)}{n}}$, i.e. section under the shadow in figure 1, then confidence interval in (3) will contain $E[y]$. At this moment, probability of event "confidence interval contains true value" is area of shadow section in figure 1, set as $(1-\alpha)$.

When model input parameter is inaccurate, output variable y may deviate. For example, expectation of y is $E[y^*]$, and sample mean value $\bar{y}(n)$ submits to distribution B in figure 1. In this condition, probability of $\bar{y}(n)$ falling into section $E[y]\pm t_{n-1,1-\alpha/2}\sqrt{\frac{S_n^2(y)}{n}}$ will decrease (to the area of curve of distribution B in the shadow), equally, probability of confidence interval $\bar{y}(n)\pm t_{n-1,1-\alpha/2}\sqrt{\frac{S_n^2(y)}{n}}$ containing $E[y]$ will decrease too which is lower than set up value $(1-\alpha)$ [7, 8].

It can be told that, when input parameter is inaccurate, reliability of stimulation output analysis conclusion will lower. Hence, this paper shall solve this issue from two aspects: adjusting mid-point of confidence interval and enlarging half width of confidence interval.

3.2.1 Adjusting mid-point of confidence interval

Firstly, it will explain the first method. In order to make it simple, let us think about the condition that in system model, it only contains one inaccurate input parameter and one output performance index. When model has more than one inaccurate parameter, concept of solving the issue is similar; when several output performance index need to be evaluated, this method could be applied to each index [9].

Suppose inaccurate parameter in model is *p*, output performance index is $E[y]$, and suppose true value of p is p_0, corresponding true value of $E[y]$ is $E[y_0]$. Now suppose stimulation modelling staff and analyst could only get one inaccurate value p^* of *p*. When input parameter p^*, value of output performance index is $E[y^*]$. Normally, it could not be told true value p_0 is bigger or smaller than mastered value p^* now, hence, it could not find out if $E[y_0]$ is bigger than $E[y^*]$, or not. In fact, as information is insufficient, it could not make mid-point of confidence interval move along the direction to $E[y_0]$. Hence, the aim could not be achieved through the first method.

This paper applies another method of adjusting on this issue: through adjustment, it could make mid-point of confidence interval move along some direction (positive direction or negative direction) to decrease maximum error (i.e. confidence interval could not contain true value) probability. Idea of this method is explained as follow.

Suppose true value p_0 of input parameter is different with p^* obtained at present, when p_0 is separately smaller or bigger than an equality of p^* (i.e. $p_0 = p^*-\Delta$ or $p_0 = p^*+\Delta, \Delta>0$), there are 3 conditions of difference between $E[y_0]$ and $E[y^*]$.

When p_0 is bigger than p^*, difference between $E[y_0]$ and $E[y^*]$ is huge, i.e.:

$$|E[y(p^*-\Delta)]-E[y(p^*)]| < |E[y(p^*+\Delta)]-E[y(p^*)]|. \quad (4)$$

When p_0 is bigger or smaller than a equality of p^*, there is no difference between $E[y_0]$ and $E[y^*]$, i.e.:

$$|E[y(p^*-\Delta)]-E[y(p^*)]| = |E[y(p^*+\Delta)]-E[y(p^*)]|. \quad (5)$$

When p_0 is smaller than p^*, difference between $E[y_0]$ and $E[y^*]$ is huge, i.e.:

$$|E[y(p^*-\Delta)]-E[y(p^*)]| > |E[y(p^*+\Delta)]-E[y(p^*)]|. \quad (6)$$

See three conditions above in (a) (b) and (c). In figure 2, suppose that there is a positive correlation between $E[y]$ and p (i.e. $E[y]$ increases as p increases), but it does not influence effect of the method.

For condition 1, it should try to make mid-point of confidence interval move to positive direction to avoid when p_0 is bigger than p^*, evaluated distance value of $E[y_0]$ is too far away, which is out of confidence interval; similarly, for condition 3, mid-point of confidence interval should move to the negative direction; for condition 2, it does not need to move.

Figure 3 takes condition 1 as example to explain the influence of moving mid-point of confidence interval on maintaining an acceptable confidence level.

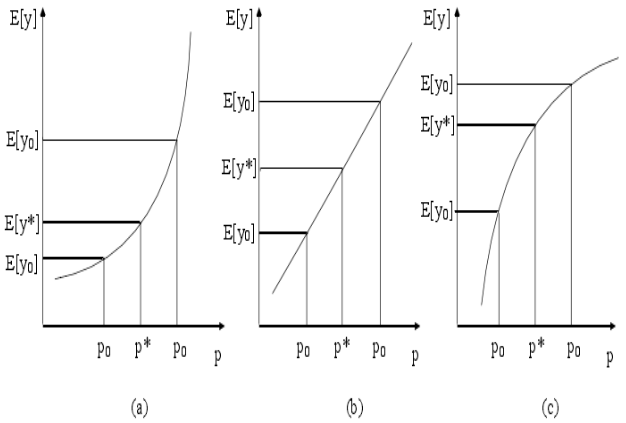

FIGURE 2 Response of $E[y]$ to p

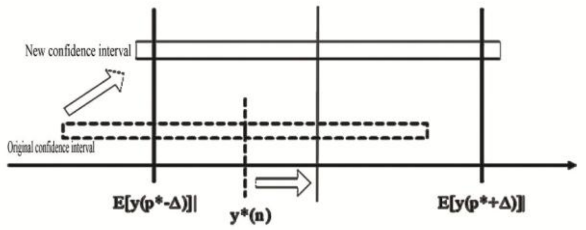

FIGURE 3 Influence of adjusting mid-point of confidence interval

It can be told from figure 3 when p_0 is bigger than p^*, original confidence interval could miss true value $E[y_0]$ with a big probability. As mid-point of confidence interval moves to positive direction, the probability shall decrease. Because in the condition 1, $E[y(p^*-\Delta)]$ is closer to mid-point of confidence interval than to $E[y(p^*+\Delta)]$. As illustrated in figure 3, new confidence interval after moving confidence interval still contains $E[y(p^*-\Delta)]$ [10, 11].

3.2.2 Enlarging half width of confidence interval

Second method of increasing confidence level is to enlarging half width of confidence interval. Obviously, this method could improve confidence level for sure.

Tough people prefer a smaller (which means accurate) confidence interval rather than a bigger section scope. But when there is not enough information, it is a safe choice for selecting a bigger confidence interval. It is more reasonable than determining a very thin confidence interval according to unreliable information.

3.3 USING RANDOM FUZZY THEORY TO SOLVE PROBLEM OF CLASSIC ANALYSIS METHOD

In order to achieve two improving methods above, this paper introduces fuzzy variable to input parameter, uses method of fuzzy discrete event system stimulation, and uses evaluation of expectation and variance of output random fuzzy variable to replace evaluation of expectation and variance of output random variable in classic method.

First of all, using mathematical expectation evaluation of output random fuzzy variable could adjust mid-point of confidence interval according to required direction. Suppose that fuzzy input parameter p has symmetrical triangle subordinating degree function, the centre of which does not locate at parameter value p^*, then subordinating degree function shape of system output performance index $E\left[y(p)\right]$ (which is fuzzy variable at here) under three conditions illustrated in figure 2 are separately illustrated in (a) (b) and (c) in figure 4.

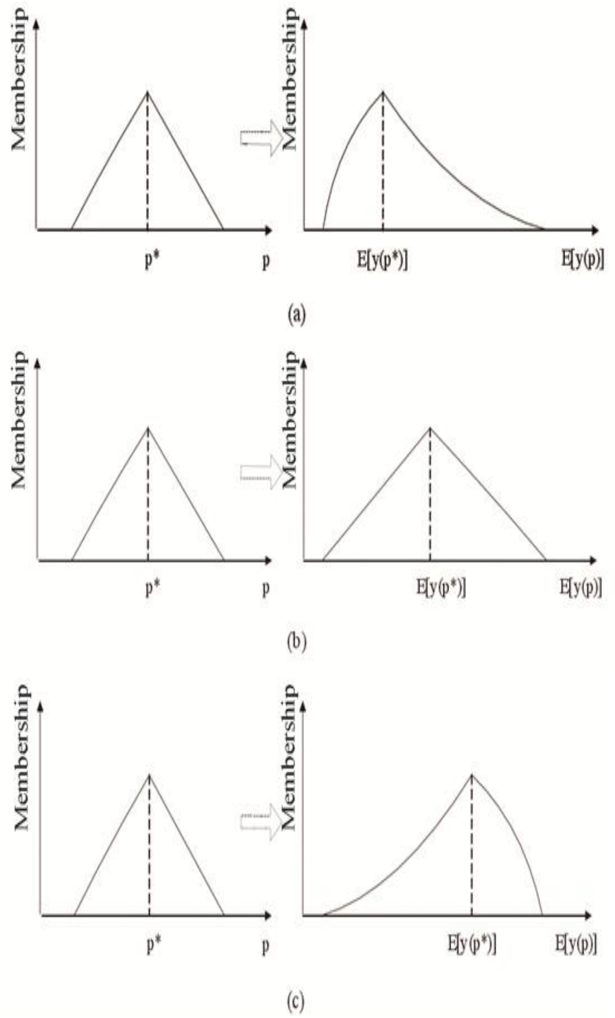

FIGURE 4 Subordinating degree functions of input parameter and output index

In figure 4 (a), expectation of $E\left[y(p)\right]$ will be bigger than $E[y(p^*)]$, because right side of $E[y(p^*)]$ has more possible value. Similarly, in figure 4 (c), expectation of $E[y(p^*)]$ will be smaller than $E[y(p^*)]$. But in figure 4 (b), $E\left[y(p)\right]$ will be equal to $E[y(p^*)]$. So centre of confidence interval shall be moved to mathematical expectation estimator position of random fuzzy variable y.

Secondly, estimator of variance of random fuzzy variable *y* is used to calculate half width of confidence interval, because *y* has two uncertainties which are randomness and fuzziness at the same time. Increasing of uncertainty could be expressed in variance of *y*.

Influence evaluation of fuzzy input parameter on output result.

4.1 ABSOLUTE INDEX OF INFLUENCE OF FUZZY INPUT PARAMETER ON OUTPUT RESULT

Influence evaluation index here is initially applied through subordinating degrees, and they form a general influence index. Suppose that system has n fuzzy input parameters: $p_1, p_2, \dots p_n$, output performance index is $\tilde{q}$. Detailed method is as follow:

(1) Divide subordinating degree into several degrees, such as $\alpha_1, \alpha_2, \dots, \alpha_k$;

(2) Make j=1;

(3) On subordinating degree α_j, α level set of each parameter $p_i\ (i=1,2,\dots n)$ is calculated based on subordinating degree of all input parameters:

$$(p_i)_{a_j} \sim I_i^j = \left[a_i^j, b_i^j\right], i=1,2,\dots,n. \quad (7)$$

(4) Perform discrete event stimulation on each parameter combination of subordinating degree α_j, calculate value of performance index $\tilde{q}$. Make $(p_1, p_2, \dots p_n) = (x_1, x_2, \dots x_n)$ in parameter combination, and mark the performance index calculated by stimulation as $\hat{q}(x_1, x_2, \dots, x_n)$.

(5) Separately calculate absolute influence index of each parameter $p_i\ (i=1,2,\dots n)$ on subordinating degree α_j:

$$\lambda_i^j = \frac{\sum_{x=b_i^j} \hat{q}(x_1, x_2, ..., x_n) - \sum_{x_i=a_i^j} \hat{q}(x_1, x_2, ..., x_n)}{2^{n-1}\left(b_i^j - a_i^j\right)}, (i=1,2,...,n). \quad (8)$$

(6) If j<k, then j=j+1, return (3);

(7) Calculate influence of fuzziness of each parameter $p_i\ (i=1,2,\dots n)$ on output performance index:

$$\lambda_i^j = \frac{\sum_{j=1}^{k} \alpha_j \lambda_i^j}{\sum_{j=1}^{k} \alpha_j}, \ (i=1,2,...,n). \quad (9)$$

4.2 RELATIVE INDEX OF INFLUENCE OF FUZZY INPUT PARAMETER ON OUTPUT RESULT

Absolute index of influence of fuzzy input parameter on output result is stated above, influence index of each parameter may has different dimension, hence, influence of each parameter could not be compared. Next, absolute index obtained based on method above shall be handled to get relative index, which could influence evaluation to meet requirement of comparison of parameters.

Mark variance of each fuzzy input parameter as $V(p_i)(i=1,2,\dots n)$, then relative index of influence of each parameter on output result is defined as follow:

$$\omega_i = \frac{\left|\lambda_i \sqrt{V(p_l)}\right.}{\sum_{l=1}^{n} \left|\lambda_l \sqrt{V(p_l)}\right.}, (i=1,2,\dots,n). \quad (10)$$

After handling like that, $\omega_i(i=1,2,\dots,n)$ are all dimensionless indexes, and satisfy:

$$\sum_{i=1}^{n} \omega_i = 1. \quad (11)$$

At this time, compare each input parameter to determine fuzziness of which parameters have more influence on performance index.

5 Stimulation experiment

In order to testify effectiveness of method above, a stimulation experiment is designed. As for a system model, it is stimulated and analysed separately by classic discrete event system stimulation and output analysis method, and fuzzy discrete event system stimulation and output analysis method provided in this paper. And results of two methods are compared.

5.1 DESCRIPTION OF MODEL

For model of 3.1 which is still being used, according to classic discrete event stimulation method, use $\bar{p}$ (5) (mean value of 5 samples) as value of parameter p; and for fuzzy discrete event model, use $\bar{p}$ (5) as centre value of fuzzy input parameter p (use symmetrical triangle subordinating degree function), and use 2 times of standard deviation of 5 samples as half width of support set of p, i.e. $p=\left[\overline{p}(5)-2\sigma_p,\overline{p}(5),\overline{p}(5)+2\sigma_p\right]$.

Confidence intervals of 90% of W_q are built by two methods separately and times and proportion of confidence interval built by two methods, which contains true value 9.9 of W_q are compared.

5.2 STIMULATION OPERATION

For model above, perform stimulation separately by classic discrete event stimulation method and fuzzy discrete event stimulation method provided in this paper and build confidence interval of 90% by corresponding output analysis method separately. In the output analysis method taken by this paper, expectation of random fuzzy variable should be calculated.

In this algorithm, for model in this experiment, reliability measuring method is as follow: suppose $E[\xi(\theta)]$ could reach minimum value a, and maximum value b, point which has a possibility of 1 is c, then if $r<c$:

$$\begin{aligned}&Cr\left\{\theta\in\Theta\left[\xi(\theta)\right]\geq r\right\}\\&=\frac{1}{2}\left(Pos\left\{E\left[\xi(\theta)\geq r\right]\right\}+Nec\left\{E\left[\xi(\theta)\right]\geq r\right\}\right)\\&=\frac{1}{2}\left(Pos\left\{E\left[\xi(\theta)\geq r\right]\right\}+1-Pos\left\{E\left[\xi(\theta)\right]\prec r\right\}\right)\\&=\frac{1}{2}\left(1+1-Pos\left\{E\left[\xi(\theta)\right]=r\right\}\right)\\&=1-\frac{1}{2}Pos\left\{E\left[\xi(\theta)\right]=r\right\}\end{aligned}\tag{12}$$

But if $r\geq c$, then:

$$\begin{aligned}&Cr\left\{\theta\in\Theta\left|E\left[\xi(\theta)\right]\geq r\right.\right\}\\&=\frac{1}{2}\left(Pos\left\{E\left[\xi(\theta)\geq r\right]\right\}+Nec\left\{E\left[\xi(\theta)\right]\geq r\right\}\right)\\&=\frac{1}{2}\left(Pos\left\{E\left[\xi(\theta)\geq r\right]\right\}+1-Pos\left\{E\left[\xi(\theta)\right]\prec r\right\}\right)\\&=\frac{1}{2}\left(Pos\left\{E\left[\xi(\theta)\right]=r\right\}+1-1\right)\\&=\frac{1}{2}Pos\left\{E\left[\xi(\theta)\right]=r\right\}\end{aligned}\tag{13}$$

Use two methods to independently perform the experiment for 100 times, and separately make statistics of times and proportion of confidence intervals which contains true value 9.9.

5.3 RESULT ANALYSIS

Experiment result is illustrated in figure 2. It can be told that only 12 of 100 confidence intervals built based on classic stimulation and output analysis method which is not using fuzzy parameter contain true value 9.9; for those which fuzzy input parameter is introduced , 86 of 100 confidence intervals built based on stimulation analysis method provided in this paper contain true value 9.9. In addition, because relationship between input and output in model of this case matches condition 1 stated in section 3.2.1, it can be told from table 2 that for the same model input parameter information, new method could make mid-point of confidence interval move to positive direction and width of confidence interval is enlarged. Hence, this method could effectively achieve the two improving method provided in this paper and finally improve reliability of result. Though confidence interval obtained is wider than the one, which does not consider fuzziness, but when information is insufficient, it is necessary cost for maintaining confidence level.

TABLE 2 Comparison of 90% confidence interval considering parameter fuzziness and not considering parameter fuzziness

Experiment times	**Fuzzy input parameter**			**Non-fuzzy input parameter**		
	Fuzzy P value	*Confidence interval*	*True value*	*P value*	*Confidence interval*	*True value*
1	[8.601,9.434,10.27]	[6.6729.971]	Y	9.434	[7.695,8.113]	N
2	[9.987,10.57,11.15]	[10.15,3.92]	N	10.57	[12.11,12.89]	N
3	[9.293,10.40,11.51]	[9.553,3.35]	Y	10.40	[11.28,12.01]	N
4	[9.385,10.06,10.74]	[7.943,11.62]	Y	10.06	[9.753,10.45]	Y
5	[8.956,10.12,11.29]	[8.323,12.12]	Y	10.12	[10.09,10.70]	N
6	[8.586,9.930,11.27]	[7.718,11.52]	Y	9.930	[9.347,9.902]	Y
7	[10.00,10.62,11.24]	[10.39,14.18]	N	10.62	[12.36,13.18]	N
8	[9.189,10.10,11.00]	[8.072,11.63]	Y	10.10	[9.986,10.60]	N
9	[8.441,9.641,10.84]	[6.494,10.28]	Y	9.641	[8.345,8.816]	N
10	[8.431,9.519,10.61]	[7.205,10.18]	Y	9.519	[7.956,8.395]	N
11	[9.514,10.48,11.44]	[9.809,13.61]	Y	10.48	[11.66,12.41]	N
12	[9.180,9.732,10.28]	[6.641,10.44]	Y	9.732	[8.647,9.142]	N
……	……	……	……	……	……	……
96	[8.265,9.851,11.44]	[7.737,11.54]	Y	9.851	[9.061,9.590]	N
97	[8.347,9.357,10.37]	[6.843,10.28]	Y	9.357	[7.467,7.868]	N
98	[8.558,9.265,9.972]	[5.184,8.976]	N	9.265	[7.134,7.587]	N
99	[8.502,9.742,10.98]	[6.883,10.68]	Y	9.742	[8.680,9.178]	N
100	[9.447,9.761,10.08]	[6.837,10.64]	Y	9.761	[8.746,9.250]	N
Correct times (Proportion)			86(86%)12(12％)			

Specifically speaking, suppose sample quantity n=5,10,20,50,100,200,500,1000, build 1000 confidence interval for each condition, and compare proportion occupied by confidence intervals (confidence level of 90%) of considering fuzziness of parameter and not considering fuzziness which cover true value. See Figure 5.

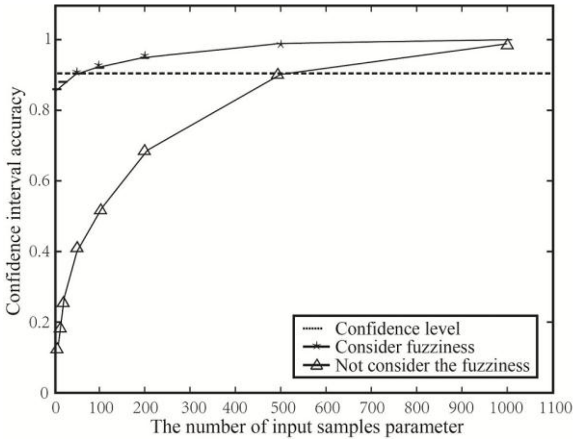

FIGURE 5 Relationship of accuracy and information quantity of confidence interval.

It could be told that when sample numbers are large, i.e. information is sufficient, both method of this paper and classic stimulation method could obtain acceptable result.

6 Conclusion

This paper uses stimulation experiment by testing influence of input parameter fuzziness on stimulation output analysis result, pointing out that fuzziness could severely deteriorate reliability of result, which is gotten by using traditional method; Furthermore, it analyses root of this deterioration and provide solution; finally, it provides new analysis method. Because numerical characteristics of statistical magnitude could often be used in statistical analysis, and stimulation method based on possible space in this paper is built based on random fuzzy theory, hence, analysis method provided in this paper uses numerical characteristics of random fuzzy variable.

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