Fuzzy Performance Measurement and Evaluation of Service Processes

Schafiq Amini, Roland Jochem

Technische Universität Berlin, Department of Quality Science

The need for interaction between customer and supplier during the production of a service makes it difficult to measure and evaluate the soft factors of a service process. They cannot be measured by using objective measuring equipment. Soft factors rather have to be measured and evaluated by people who function as subjective measuring equipments. The use of Likert scales is the common way to measure and evaluate soft factors. But they do not sufficiently consider human perception. The current paper presents a conceptual five stage model based on the fuzzy set theory to objectify the measurement and evaluation procedure of service processes.

1. Introduction

The service sector becomes more and more important in worlds´ leading economies. Simultaneously the competition between service companies increases. In order to succeed against the competition service companies have to put the aspect of customer orientation and the process-oriented way of thinking in the foreground. Like industrial companies service companies must visualize and optimize their processes depending on customer requirements. In opposite to an industrial process a service process is characterized by the interaction between customers and suppliers. Therefore the success of a service process is especially dependent on the performance of soft factors. In this context the biggest challenge is the measurement and evaluation of these soft factors. Common method is the deployment of Likert scales. The disadvantage of using Likert scales is that one reduces the human perception on one concrete number (Chen, 2001). This approach doesn´t correspond to the reality. To consider human perception the fuzzy set theory is used. Fuzzy sets are an extension of the classical notion of sets and were introduced by *Lotfi A. Zadeh*. The following example illustrates the practical benefit of fuzzy sets.

The given set “tall people” has elements in the interval between 180cm to 210cm. The membership of one element to the set of “tall people” is defined with 1. The non-membership is defined with 0. Every element, which is outside of the defined interval, is no element of the set “tall people”. In the classical set theory an element either belongs to a set or it does not. In Fig. 1 the Element 179cm doesn’t belong to the defined set of “tall people”.

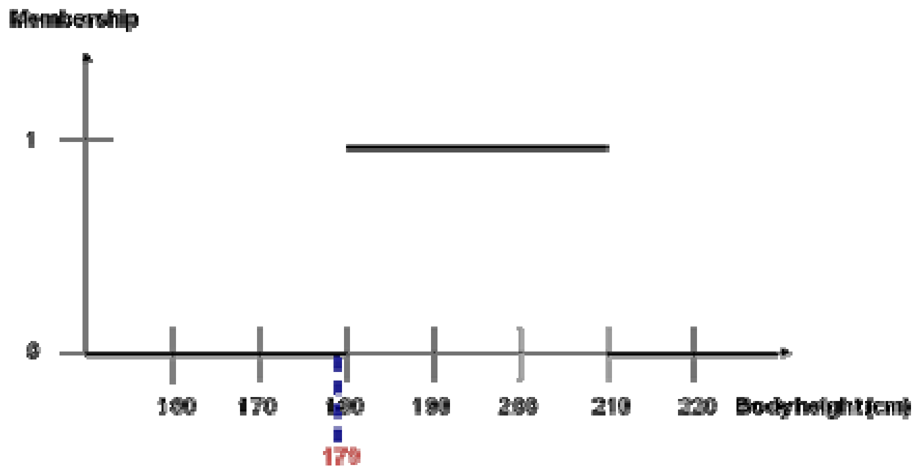

Fig. 1: Classical set "tall people"

The sharp transition from "tall people" to "not tall people" does not correspond to human perception. The fuzzy set theory allows a number to belong gradually to a set. To define the membership of an element x to the set A the following function is defined in the context of fuzzy sets:

$$\mu_A(x) = \{1 \; for \; x \in A, \; 0 \; for \; x \notin A\} \tag{1}$$

In the classical set theory the function only accepts the values 0 and 1. In the context of the fuzzy set theory the function is a membership function, which accepts values in the interval [0, 1] (Biewer, 1997). Every element of the basic set G has a certain grade of membership ($0 \leq \mu \leq 1$) to the set „tall people". The membership grade is determined by experts. Within the example the membership function of the set "tall people" could have the following form:

$$\mu_{tallpeople}(x) = \begin{pmatrix} 0 & x < 170 \\ \frac{1}{40}x - 4.25 & 170 \leq x \leq 210 \\ 1 & x > 210 \end{pmatrix} \tag{2}$$

Now the element 179cm belongs to the set "tall people" with the grade

$$\mu_{tallpeople}(179) = 0.225. \tag{3}$$

This result rather meets the human perception of "tall people" (Fig. 2).

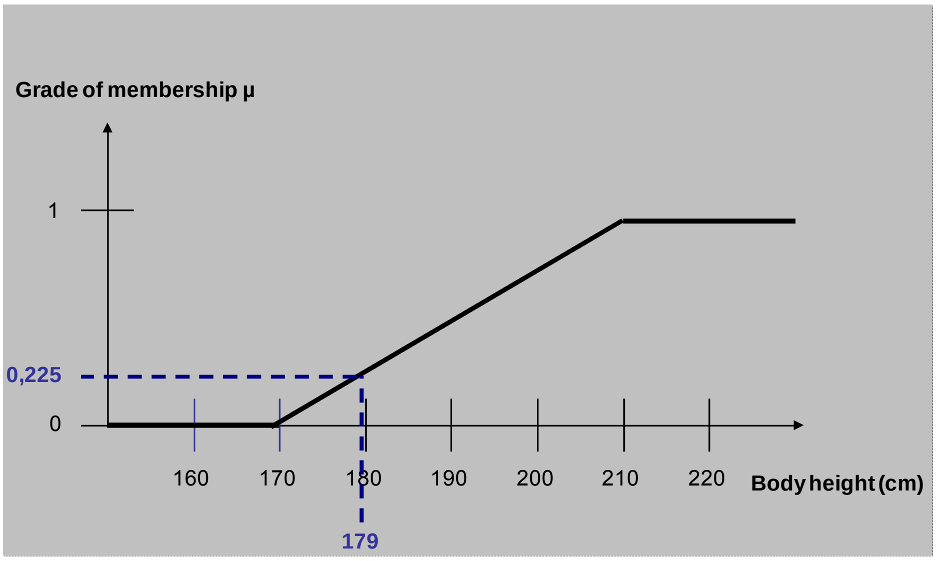

Fig. 2: Fuzzy set “tall people”

In the following chapter a conceptual measurement and evaluation model for service processes is introduced, which is based on the fuzzy set theory.

2. The Conceptual Model

The conceptual model is subdivided into the following five parts:

- Process visualization and process description
- Definition of performance measures
- Weighting of performance measures
- Measurement and evaluation
- Performance measures consolidation and process performance calculation

2.1. Process visualization and process description

Within the visualization of service processes it is necessary to point out activities with an interaction between customers and suppliers. The Service Blueprinting is a very powerful tool. It distinguishes activities between customers and suppliers from internal activities of the company and was designed by *Shostack* at the beginning of the 1980s (Shostack, 1982). The Service Blueprinting consists of at least three parts separated from each other using the line of visibility and the line of interaction. The line of interaction separates activities with interaction between customer and supplier from internal activities. The line of visibility differs between activities which are visible for the customer from invisible activities. The main drawback of Service Blueprinting is that there are no information about the customer or the supplier of the process and the process input and process output is not visible. To eliminate these drawbacks the

Service Blueprinting should be extended by the SIPOC- Diagram. SIPOC is the abbreviation of supplier, input, process, output, customer and it is an important Six Sigma tool during the define phase (Lunau et al., 2006, 24). The Service Blueprinting replaces the common process illustration in the SIPOC-Diagram. In this context an extended Service Blueprinting gives an overview of the service process, its inputs and outputs, as well as its customers and suppliers. (see example in Fig. 3).

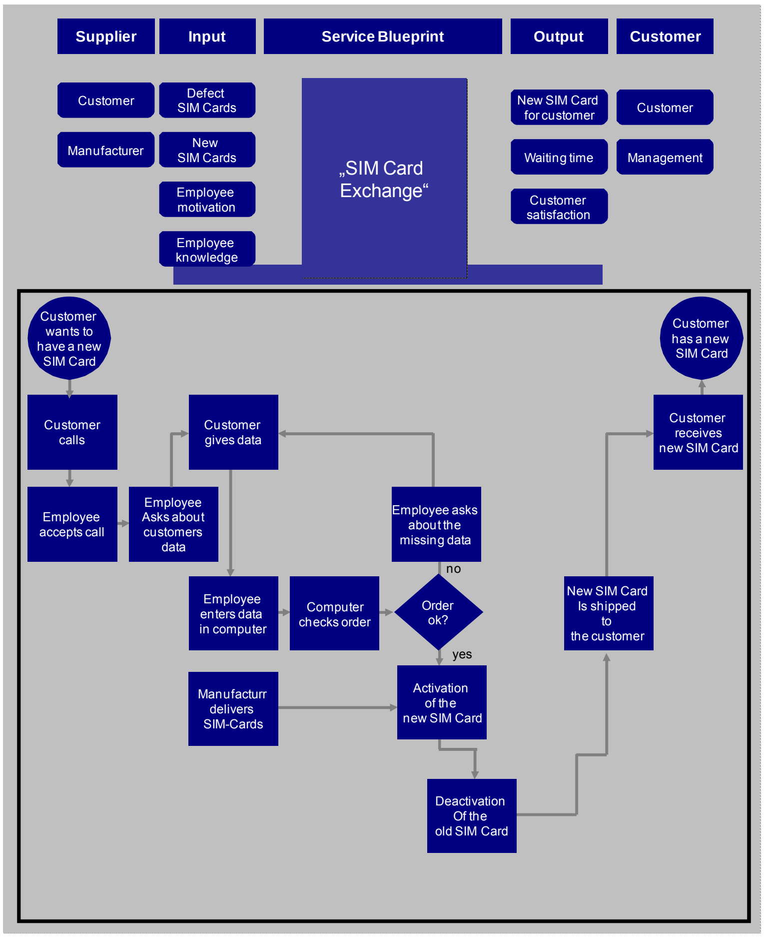

Fig. 3: Extended Service Blueprinting for the Process “SIM Card Exchange”

2.2. Definition of performance measures

The definition of performance measures is based on the identified customers of the process. The organization has to find out the requirements of the customers. Therefore it can use existing data (reactive data determination) or it can perform a customer survey (proactive data determination) (Theodorovics, 2006). The next step is to transform the critical to customers (CTC, the customer requirements) to the critical to qualities (CTQ, critical quality characteristics) by using the CTC-CTQ-driver-tree. The major challenge is to find out the right drivers for the transformation of the CTCs to the CTQs. The CTQs should be the basis to measure the process performance. Process performance is based on the following three dimensions: Quality, Time, Costs. At the same time these three dimensions are the drivers to transform CTCs to CTQs (Fig. 4).

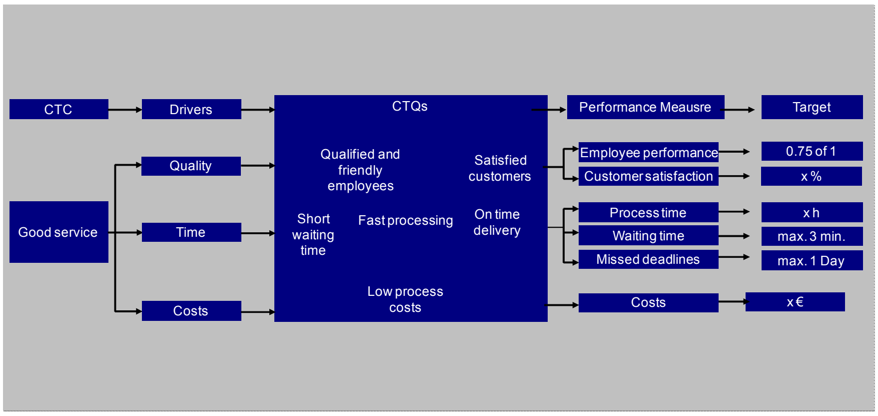

Fig. 4: Exemplary CTC-CTQ-Driver-Tree

2.3. Weighting of performance measures

In this phase the weights of the performance indicators are defined. The common practice is the use of the direct ratio procedure (Eisenführ, 2003, 124). Within the framework of this procedure the first step is to define the priority of the performance measures. Then the performance measures are subjected to a pairwise comparison to get their relative importance. Finally the defined weights must undergo a consistency check. In reality it is nearly impossible to have consistent preferences of the decision-makers (e.g. because they are not able to decide rationally) (Rommelfänger, Eickemeier, 2002, 153). But in the context of the direct-ratio-procedure it is necessary to have consistency. One method, which tolerates a certain level of inconsistency is the Analytical Hierarchy Process (AHP) (Rommelfänger, Eickemeier, 2002). The AHP was first defined by *Thomas L. Saaty*. It allows determining the weights of criterions and therefore also the weights of performance measures (Entani et al., 2006). The special feature of AHP is the definition of a consistency ratio, which represents the degree of consistency of a decision process. Basically the AHP has a multi-stage hierarchical structure. In the context of weighting performance measures there is just one stage of hierarchy (Fig. 5).

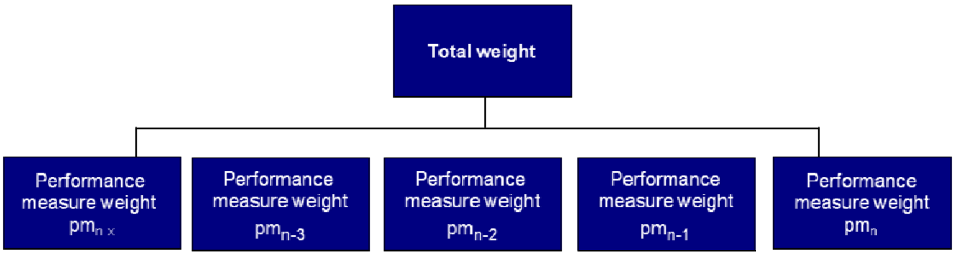

Fig. 5: One-Level-AHP-Structur for performance weights

For the definition of the weights the decision makers evaluate the importance of a performance measure in contrast to another one. Therefore they use the nine-point-scale of *Saaty* (Table 1).

Value	Numerical Rating
Equally preferred	1
Moderately preferred	3
Strongly preferred	5
Very strongly preferred	7
Extremly preferred	9
Intermediate values	2,4,6,8

Table 1: Nine-point-scale of Saaty

The result of the evaluation is a pairwise comparison matrix, which represents the preferences of the decision makers (Table 2).

	Performance Measure A	Performance Measure B	Performance Measure C
Performance Measure A	1	1/7	1/2
Performance Measure B	7	1	3
Performance Measure C	2	1/3	1

Table 2: Pairwise comparison Matrix

The eigenvector of the largest eigenvalue of the pairwise comparision matrix describes the performance measure´s weights. To determine the consistency *Saaty* developed the consistency-index which has the following definition:

$$CI = \frac{\lambda_{\max} - n}{n-1}. \tag{4}$$

The consistency index is put in relation to the random index (ri), which is a randomly defined consistency index.

n	**1**	**2**	**3**	**4**
RI (n)	0	0	0,58	0,9
n	**5**	**6**	**7**	**8**
RI(n)	1,12	1,24	1,32	1,41
n	**9**	**10**	**11**	**12**
RI (n)	1,45	1,48	1,51	1,56
n	**13**	**14**	**15**	
RI (n)	1,56	1,57	1,5	

Table 3: RI-Table

The pairwise comparison matrix is consistent, if the following quotation is fulfilled:

$$CV(n) = \frac{CI(n)}{RI} \leq 0{,}1 \tag{5}$$

The usage of the AHP is very popular due to the possibility to analyze the degree of inconsistency and the logical structure of AHP (Roth, 1998). Nevertheless the major drawback of the AHP is that inaccuracies and uncertainties shall not be taken into account during the transformation of the decision makers´ preferences in a concrete number (Deng, 1999, 216; Kwong, Bai, 2003, 620; Tsetinov, Mikhailov, 2004, 553; Yang, Chen, 2004, 204). AHP represents decisions and preferences as exact numbers in a nine-point-scale. In most practical situations decision makers are not able to assess how much one criterion is more important than another one (Tsetinov, Mikhailov, 2004, 553). Preferences of decision makers only can be assessed in orders of magnitudes (Rommelfänger, Eickemeier, 2002, 163). The fuzzy set theory helps to consider theses preferences. In the following the AHP is extended by fuzzy sets. In opposition to the classical AHP the fuzzy AHP replaces the nine-point-scale with triangular fuzzy numbers. The following example demonstrates the fuzzy AHP. Therefore the decision makers create nine triangular fuzzy numbers, which illustrate their preferences (Fig. 6).

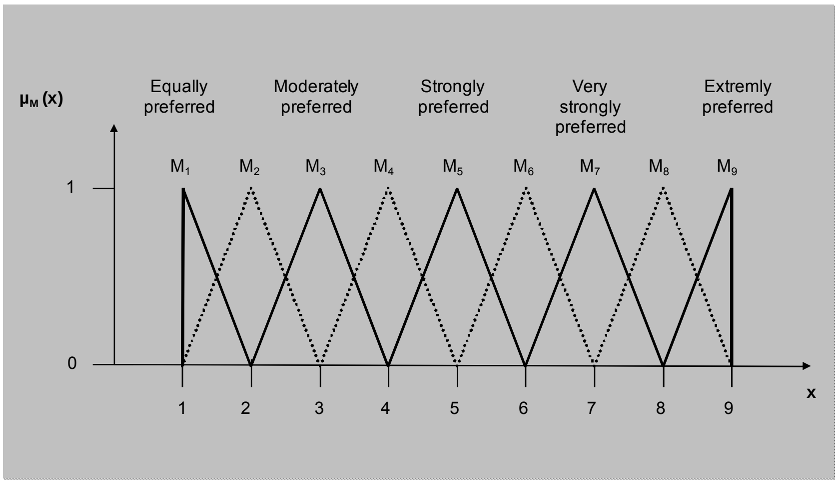

Fig. 6: Triangular fuzzy numbers (Rommelfänger, Eickemeier, 2002)

Every triangular fuzzy number can be formulated with the aid of its 1-level set and its limit values (Traeger, 1994). The 1-level set describes the values of the triangular fuzzy number, which have a membership of one. The limit values describe the borders of the triangular fuzzy number. For example the triangular fuzzy number M_1 in Fig. 4 is defined as M_1= (1, 1, 2). The first and the last value are the limit values and the value in the center describes the 1-level set. In the context of AHP the reciprocal values of the nine-point-scale are also used for the pairwise comparison. The reciprocal value of a triangular fuzzy number is formed by the following rule:

$$M_x = (l, m, u) \Rightarrow \frac{1}{M_x} = (\frac{1}{u}, \frac{1}{m}, \frac{1}{l}). \tag{6}$$

The reciprocal value of the triangular fuzzy number M_1 would be:

$$\frac{1}{M_1} = (\frac{1}{2}, \frac{1}{1}, \frac{1}{1}). \tag{7}$$

With the defined triangular fuzzy numbers the decision makers can carry out the pairwise comparison of the performance measures. The result is a fuzzy pairwise comparison matrix with the preferences of all decision makers (Table 4).

	Performance measure A	Performance measure B	Performance measure C
Performance measure A	(1, 1, 1)	(1, 2, 3) (2, 3, 4)	(1, 1, 2) (1, 1, 2)
Performance measure B	(1/3, 1/2, 1/1) (1/4, 1/3, 1/2)	(1, 1, 1)	(1, 1, 2) (1, 2, 3)
Performance measure C	(1/2, 1/1, 1/1) (1/2, 1/1, 1/1)	(1/2, 1/1, 1/1) (1/3, 1/2, 1/1)	(1, 1, 1)

Table 4: Fuzzy pairwise comparison matrix

The next step will be the calculation of the arithmetic mean of the preferences (Table 5).

	Performance measure A	Performance measure B	Performance measure C
Performance measure A	(1, 1, 1)	(2, 3, 4)	(1, 1, 2)
Performance measure B	(1/4, 1/3, 1/2)	(1, 1, 1)	(1,2, 3)
Performance measure C	(1/2, 1/1, 1/1)	(1/3, 1/2, 1/1)	(1, 1, 1)

Table 5: Arithmetic mean of the decision makers´ preferences

Now it is necessary to get the maximum eigenvalue of the matrix (Table 5) to calculate the degree of consistency. Therefore the matrix is transformed in sharp numbers with the following formula (Kwong, Bai, 2006, 622):

$$M_{Sharp} = \frac{4m + l + u}{6}. \quad (8)$$

The result of the transformation is the following matrix:

	Performance measure A	Performance measure B	Performance measure C
Performance measure A	1	2	1,16
Performance measure B	0,45	1	1,58
Performance measure C	0,92	0,73	1

Table 6: Matrix with sharp values

To get the eigenvalues λ of the matrix the following system of equations must be solved:

$$(M - \lambda E)x = 0. \quad (9)$$

M describes the matrix, λ describes the eigenvalue of Matrix M, E is the unit matrix and x describes the eigenvectors of the matrix M. The system of equation is solvable under the following condition:

$$\det(A - \lambda E) = 0. \quad (10)$$

This determinant is a polynomial grade n. Its roots describe the searched eigenvalues. The maximum eigenvalue of the matrix in Table 6 is calculated as follows:

$$M = \begin{pmatrix} 1 & 2 & 1.16 \\ 0.45 & 1 & 1.58 \\ 0.92 & 0.73 & 1 \end{pmatrix} \Rightarrow \det(M - \lambda E) = 0 \Rightarrow \begin{pmatrix} 1-\lambda & 2 & 1.16 \\ 0.45 & 1-\lambda & 1.58 \\ 0.92 & 0.73 & 1-\lambda \end{pmatrix} =$$

$$(1-\lambda)^3 + 2 * 1.58 * 0.92 + 1.16 * 0.45 * 0.73 - 0.92 * (1-\lambda) * 1.16 -$$

$$0.73 * 1.58 * (1-\lambda) - (1-\lambda) * 0.45 * 2 = (1-\lambda)^3 - 3.12 * (1-\lambda) + 3.28$$

$$\Rightarrow \lambda_1 = 3.15548 = \lambda_{max} \tag{11}$$

The matrix has only one eigenvalue. This eigenvalue is simultaneously the maximum eigenvalue of the matrix. The calculation of the consistency index is as follows:

$$CI = \frac{3.15548 - 3}{3 - 1} = 0.0774. \tag{12}$$

The consistency value is:

$$CV(n) = \frac{0.0774}{0.58} \approx 0.1. \tag{13}$$

To calculate the weights of the performance measures the procedure of *Chang* is used (Chang, 1996). Every triangular fuzzy number is described with the value $T_{ij.}$ The index i describes the vertical position and the index j the horizontal position of the triangular fuzzy number. The result is the following matrix:

	Performance measure A	Performance measure B	Performance measure C
Performance measure A	T_{11}	T_{12}	T_{13}
Performance measure B	T_{21}	T_{22}	T_{23}
Performance measure C	T_{31}	T_{32}	T_{33}

Table 7: Fuzzy Matrix with Variable Tij

The next step is the consolidation of the triangular fuzzy numbers using the following formula:

$$S_i = \sum_{j=1}^{m} T_{ij} * \left[\sum_{i=1}^{n} \sum_{j=1}^{m} T_{ij} \right]^{-1}. \tag{14}$$

The consolidation of the values in Table V is calculated as follows:

$$S_1 = (3.5, 4.5, 6.5) * \left[\frac{1}{13.75}, \frac{1}{10.17}, \frac{1}{7.71} \right] = (0.25, 0.44, 0.84),$$
$$S_2 = (2.29, 2.92, 4{,}25) * \left[\frac{1}{13.75}, \frac{1}{10.17}, \frac{1}{7.71} \right] = (0.16, 0.28, 0.55),$$
$$S_3 = (1.92, 2.75, 3) * \left[\frac{1}{13.75}, \frac{1}{10.17}, \frac{1}{7.71} \right] = (0.13, 0.27, 0.38). \tag{15}$$

The consolidated triangular fuzzy numbers are compared with each other. Therefore the following formula is used:

$$V(S \geq S_1,..., S_n) = V[(S \geq S_1)\ AND ... AND\ (S \geq S_N)] = \min V(S \geq S_i),$$
$$i = 1,2,..n.$$

$$V(S_1 \geq S_2) = 1\ if\ m_1 \geq m_2; V(S_2 \geq S_1) = \frac{l_1 - u_2}{(m_2 - u_2) - (m_1 - l_1)}. \quad (16)$$

The results of the comparison of the consolidated triangular fuzzy numbers are the following values:

$$V(S_1 \geq S_2) = 1; \quad V(S_1 \geq S_3) = 1; \quad V(S_2 \geq S_3) = 1;$$
$$V(S_2 \geq S_1) = \frac{0.25 - 0.55}{(0.28 - 0.55) - (0.44 - 0.25)} = \frac{-0.3}{-0.46} = 0.65,$$
$$V(S_3 \geq S_1) = \frac{0.25 - 0.38}{(0.27 - 0.38) - (0.44 - 0.25)} = \frac{-0.13}{-0.3} = 0.43,$$
$$V(S_3 \geq S_2) = \frac{0.16 - 0.38}{(0.27 - 0.38) - (0.28 - 0.16)} = \frac{-0.12}{-0.23} = 0.52. \quad (17)$$

The values of the comparison grades are as listed below:

$$\min V(S_1 \geq S_2, S_3) = (1, 1) = 1,$$
$$\min V(S_2 \geq S_1, S_3) = (0.65, 1) = 0.65,$$
$$\min V(S_3 \geq S_1, S_2) = (0.43, 0.52) = 0.43. \quad (18)$$

The following weight vector is the result of the comparison grades:

$$W = (1, 0.65, 0.43). \quad (19)$$

The last step is to calculate the normalized vector:

$$W = (\frac{1}{1 + 0.65 + 0.43}, \frac{0.65}{1 + 0.65 + 0.43}, \frac{0.43}{1 + 0.65 + 0.43}) = (0.48, 0.31, 0.21). \quad (20)$$

The normalized values describe the weights of the performance measures A, B and C.

2.4. Measurement and evaluation

The concept of membership function is the basis to define evaluation functions for the performance measures. Therefore all decision makers determine together the main values of the function. This way the whole expertise of the decision makers is considered. The inputs of the evaluation function are sigma values (sigma values simply allow comparing measures with each other. Furthermore sigma values consider standard deviations in the calculation). The outputs of the function are performance values between 0 and 1. The decision makers determine which sigma values are acceptable for each performance measure. They define the minimal acceptable sigma value for each performance measure with the performance value of 0.05. Furthermore they define the minimum sigma value, which already fulfils a performance value of 1. In this way enterprises can constitute efficiently their resources. Furthermore the definition of the evaluation function has to be compatible with the customer requirements.

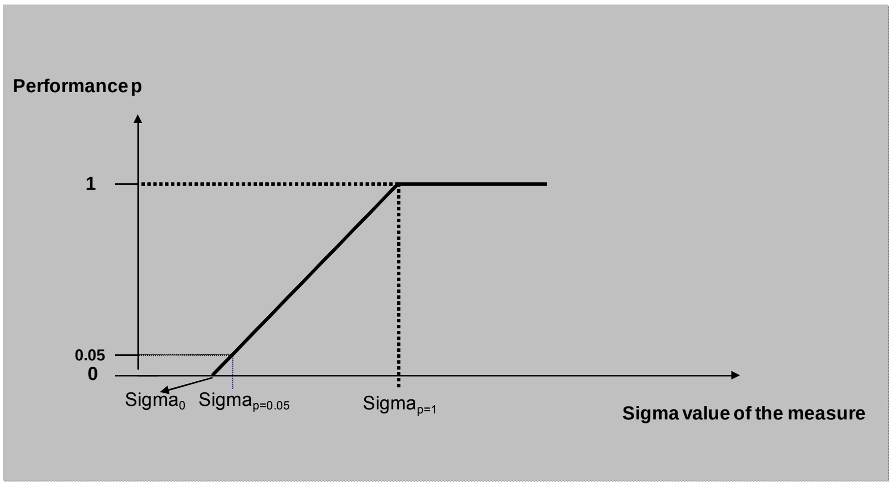

Fig. 7: Evaluation Function

The mathematical notation of the evaluation function is as follows:

$$p_{measure}(Sigma) = \{Sigma,\ p_{measure} > \alpha,\ \alpha \geq 0.05\},$$

$$p_{measure}(Sigma) = \begin{pmatrix} m*(Sigma)+n & for\ Sigma_0 \leq Sigma \leq Sigma_{p=1} \\ 1 & for\ Sigma-Value > Sigma_{p=1} \end{pmatrix},$$

$$m = \left(\frac{1-0.05}{Sigma_{p=1} - Sigma_{p=0.05}}\right),\ n = Sigma_{p=1} - m*(Sigma),\ \ Sigma_0 = \frac{-n}{m}. \qquad (21)$$

The next step is the determination of the measurement method. It is important to differ between quantitative and qualitative performance measures. Quantitative performance measures are not influenced by subjective decisions of the decision makers. They are measured by means of objective measuring instruments. Numeric values for qualitative performance measures do not exist. Therefore the opinion of decision makers (acting as measuring instruments) has to be transformed into numeric values. During the transformation process it is important, that the numeric values describe adequately the information structure. A common method is the usage of rating scales (e.g. Likert scales). Main drawback of these scales is the high loss of information during the transformation of the decision makers´ subjective opinions to numeric values. In the following, *Chen´s* concept of linguistic variables (based on the fuzzy set theory) is used to counteract the information loss in order to evaluate the characteristics of the qualitative performance measures (Chen, 2001).

The first step is the definition of an assessment scale and an importance scale, which are based on trapezoidal fuzzy intervals and linguistic variables. The quintuple (A(x), T(A), U, G, M) defines the linguistic variable A in the following way:

- A (x): x1= assessment scale; x2=importance scale
- Linguistic terms: T(A(x1)) = (absolutely bad, very bad, bad, average, good, very good, excellent); T(A(x2))= (no importance, very little importance, little

importance, average importance, high importance, very high importance, ab solutely high importance)

- Domain: U(A(x1))= [0,10] ; U(A(x2))=[0, 1]
- No syntactical rules defined: G = empty set
- Linguistic terms are defined by trapezoidal fuzzy intervals: M= trapezoidal fuzzy intervals.

The tables 8 and 9 show the assessment and importance scale.

Linguistic term	Trapezoidal fuzzy interval
absolutly bad	(0, 0, 0, 0)
very bad	(0, 0, 1, 2)
bad	(1, 2, 3, 4)
average	(3, 4, 5, 6)
good	(5, 6, 7, 8)
very good	(7, 8, 9, 10)
excellent	(9,10,10,10)

Table 8: Assessment scale

Linguistic term	Trapezoidal fuzzy interval
no importance	(0.0, 0.0, 0.0, 0.0)
very little importance	(0.0, 0.1, 0.2, 0.3)
little importance	(0.2, 0.3, 0.4, 0.5)
average importance	(0.4, 0.5, 0.6, 0.7)
high importance	(0.6, 0.7, 0.8, 0.9)
very high importance	(0.8, 0.9, 1, 1)
abolutely high importance	(1,1,1,1)

Table 9: Importance scale

In the next step, every decision maker determines the importance w and the grade of performance x of the qualitative performance measures using the scales in table 8 and 9. The result is a matrix for the importance and one for the assessment:

$$X = \begin{bmatrix} x_{11} & x_{12} & \dots & x_{1m} \\ x_{21} & x_{22} & \dots & x_{2m} \\ . & . & \dots & . \\ . & . & \dots & . \\ . & . & \dots & . \\ . & . & \dots & . \\ x_{n1} & x_{n2} & \dots & x_{nm} \end{bmatrix}, \quad W = \begin{bmatrix} w_{11} & w_{12} & \dots & w_{1m} \\ w_{21} & w_{22} & \dots & w_{2m} \\ . & . & \dots & . \\ . & . & \dots & . \\ . & . & \dots & . \\ . & . & \dots & . \\ w_{n1} & w_{n2} & \dots & w_{nm} \end{bmatrix}. \quad (22)$$

To get a total value for one qualitative performance measure the arithmetic mean of the matrices is calculated:

$$\tilde{X} = [\tilde{x}_1 \quad \tilde{x}_2 \quad \dots \quad \tilde{x}_m] \quad , \quad \tilde{W} = [\tilde{w}_1 \quad \tilde{w}_2 \quad \dots \quad \tilde{w}_m] \tag{23}$$

Then the characteristic matrix will be normalized:

$$\tilde{x}_k = (a_k, b_k, c_k, d_k)\,,\ \tilde{n}_k = \left(\frac{a_k}{d_k^*}, \frac{b_k}{d_k^*}, \frac{c_k}{d_k^*}, \frac{d_k}{d_k^*}\right),\ d_k^* = \max d_k\,. \tag{24}$$

The calculation formula of the total value is as follows:

$$\tilde{P} = \frac{1}{m} * \{(\tilde{n}_1 * w_1) + (\tilde{n}_2 * \tilde{w}_2) * \dots * (\tilde{n}_m + \tilde{w}_m)\}. \tag{25}$$

The total value is a trapezoidal interval and has to be transformed to a sharp number with the following formula:

$$d(I,\tilde{P}) = \sqrt{\frac{1}{4}[(1-p_1)^2 + (1-p_2)^2 + (1-p_3)^2 + (1-p_4)^2]}. \tag{26}$$

$$Totalvalue = 1 - d(I,\tilde{P}). \tag{27}$$

The last steps are to determine the sigma-value of the performance measure and to integrate the sigma-value in the evaluation-function.

The following example illustrates the phase 4:

Three decision makers evaluate the qualitative process performance measure “employee performance”, which consists the following criterions:

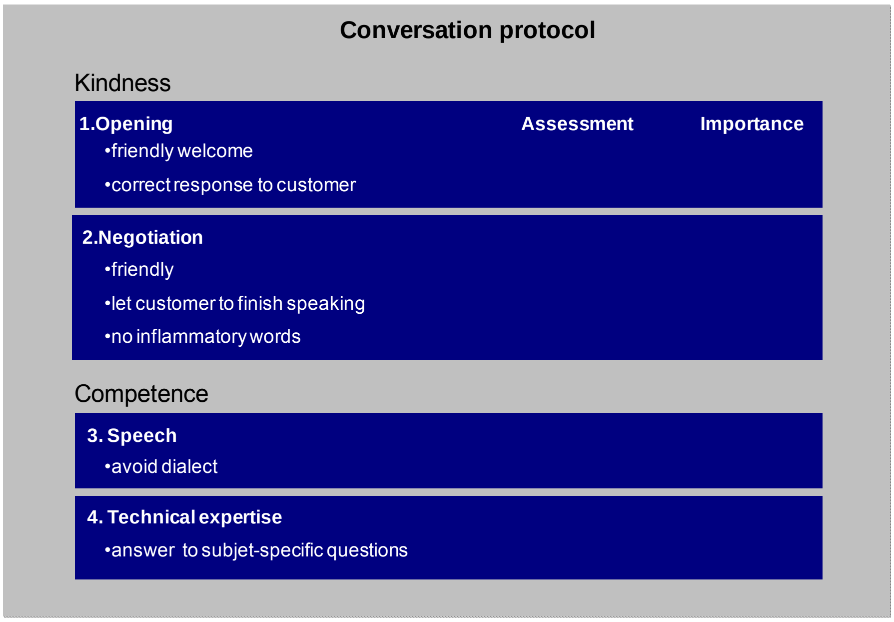

Fig. 8: Criterions of the performance measure “employee performance”

Every decision maker evaluates one employee. One measured value is calculated by the consolidation of the three decision makers´ evaluations (Table 10).

Assessment matrix

	friendly welcome	correct responce to customer	friendly	let customer to finish speaking	no inflammatory words	avoids dialect	answers to subject-specific questions
Decision Maker 1	(5, 6, 7, 8)	(7, 8, 9, 10)	(7, 8, 9, 10)	(9, 10, 10, 10)	(3, 4, 5, 6)	(1, 2, 3, 4)	(1, 2, 3, 4)
Decision Maker 2	(5, 6, 7, 8)	(5, 6, 7, 8)	(3, 4, 5, 6)	(3, 4, 5, 6)	(7, 8, 9, 10)	(3, 4, 5, 6)	(1, 2, 3, 4)
Decision Maker 3	(9, 10, 10, 10)	(7, 8, 9, 10)	(5, 6, 7, 8)	(9, 10, 10, 10)	(5, 6, 7, 8)	(5, 6, 7, 8)	(7, 8, 9, 10)

Importance matrix

	friendly welcome	correct responce to customer	friendly	let customer to finish speaking	no inflammatory words	avoids dialect	answers to subject-specific questions
Decision Maker 1	(0.4, 0.5, 0.6, 0.7)	(1, 1, 1, 1)	(0.8, 0.9, 1, 1	(1, 1, 1, 1)	(0.4, 0.5, 0.6, 0.7)	(0.8, 0.9, 1, 1)	(0.4, 0.5, 0.6, 0.7)
Decision Maker 2	(0.4, 0.5, 0.6, 0.7)	(1, 1, 1, 1)	(0.8, 0.9, 1, 1	(1, 1, 1, 1)	(0.8, 0.9, 1, 1)	(0.4, 0.5, 0.6, 0.7)	(0.8, 0.9, 1, 1)
Decision Maker 3	(0.4, 0.5, 0.6, 0.7)	(0.8, 0.9, 1, 1)	(0.8, 0.9, 1, 1	(0.4, 0.5, 0.6, 0.7)	(0.8, 0.9, 1, 1)	(0.4, 0.5, 0.6, 0.7)	(0.8, 0.9, 1, 1)

Table 10: Assessment and importance matrix

The next step is the consolidation of the values (23).

Assessment of the criterions

firendly welcome	correct responce to customer	friendly	let customer to finisch speaking	no inflammatory words	avoid dialect	answers to subject-specific questions
(6.33, 7.33, 8, 8.67)	(6.33, 7.33, 8.33, 9.33)	(5, 6, 7, 8)	(7, 8, 8.33, 8.67)	(5, 6, 7, 8)	(3, 4, 5, 6)	(3, 4, 5, 6)

Importance of the criterions

firendly welcome	correct responce to customer	friendly	let customer to finisch speaking	no inflammatory words	avoid dialect	answers to subject-specific questions
(0.3, 0.4, 0.5, 0.6)	(0.93, 0.97, 1, 1)	(0.8, 0.9, 1, 1)	(0.8, 0.9, 1, 1)	(0.53, 0.77, 0.87, 0.9)	(0.53, 0.63, 0.73, 0.8)	(0.67, 0.77, 0.87, 0.9)

Table 11: Consolidated assessment and importance matrix

Subsequently the assessment matrix is normalized (24), which is then multiplied with the importance matrix to get weighted criterions (Table 12).

Normalized asessment matrix

friendly welcome	correct responce to customer	friendly	let customer to finish speaking	no inflammatory words	avoids dialect	answers to subject-specific questions
(0.68, 0.79, 0.86, 0.93)	(0.68, 0.79, 0.89, 1)	(0.54, 0.64, 0.75, 0.86)	(0.75, 0.86, 0.89, 0.93)	(0.54, 0.64, 0.75, 0.86)	(0.32, 0.43, 0.54, 0.64)	(0.32, 0.43, 0.54, 0.64)

Weighted, normalized evaluation of the criterions

friendly welcome	correct responce to customer	friendly	let customer to finish speaking	no inflammatory words	avoids dialect	answers to subject-specific questions
(0.20, 0.32, 0.43, 0.56)	(0.63, 0.77, 0.89, 1)	(0.43, 0.58, 0.75, 0.86)	(0.6, 0.78, 0.89, 0.93)	(0.29, 0.49, 0.65, 0.77)	(0.17, 0.27, 0.39, 0.51)	(0.21, 0.33, 0.47, 0.58)

Table 12: Normalized assessment and importance matrix

The weighted, normalized fuzzy intervals are added together and then divided by the number of criterions (25). The result is a fuzzy total measurement of

$$\widetilde{P} = (0.36, 0.51, 0.64, 0.74) \tag{28}$$

Eq. 28 has to be transformed to a sharp value (26):

$$d(I, \widetilde{P}) = \sqrt{\frac{1}{4}[(1-0.36)^2 + (1-51)^2 + (1-64)^2 + (1-74)^2]}$$

$$= 0.46 \rightarrow 1 - 0.46 = 0.54. \tag{29}$$

The calculated value for the employee performance is 0.54. The next step is the calculation of the sigma level. The assumption is that an organization determined data over a certain time period.

Calculation of the sigma value for the performance measure “employee performance” (Magnusson et al., 2004; Magnusson et al., 2001):

- Calculated values (The values should be calculated over a certain period of time):

0,54	0,8	0,9	0,9	0,8	0,8
0,88	0,55	0,89	0,84	0,94	0,9
0,69	0,78	0,91	0,82	0,78	0,73
0,81	0,82	0,85	0,94	0,82	0,79
0,89	0,92	0,76	0,73	0,88	0,82

- Mean and standard deviation:

$$\bar{x} = \frac{1}{n}\sum_{i=1}^{n} x_i = 0.82\,, \quad s = \sqrt{\frac{\sum_{i=1}^{n}(x_i - \bar{x})}{n-1}} = 0.10 \qquad (30)$$

- Z-Value of upper specification limit ZUSL:

$$Z_{USL} = \frac{USL - \bar{x}}{s} \qquad (31)$$

- Upper specification limit not available
- Z-Value of lower specification limit ZLSL:

$$Z_{LSL} = \frac{\bar{x} - LSL}{s} = \frac{0.82 - 0.75}{0.1} = 0.7 \qquad (32)$$

- Error probability (ZUSL and ZLSL are transformed to error probability value with the aid of a standard normal distribution table):

$$p(d)LSL = 0.0242 \qquad (33)$$

- dpmo-value:

$$dpmo = p(d)LSL * 1.000.000 = 0.0242 * 1.000.000 = 24200 \qquad (34)$$

- Calculation of the sigma value (Breyfogle, 2003):

$$Sigmavalue = 0.8406 + \sqrt{29.37 - 2.221 * \ln(24200)} \approx 3.48\, Sigma \qquad (35)$$

The next step is the integration of the sigma value into the evaluation function. The assumption is that decision makers determine the following values for the evaluation function:

- Performance p=0.05 → $sigma_{p=0.05}$= 2.0,
- Performance p=1 → $sigma_{p=1}$= 4.5.

Then the evaluation function has the following form:

$$p_{employeeperformance}(Sigma) = \{Sigma, p_{employeeperfomance} > \alpha, \alpha \geq 0.05\},$$

$$p_{employeeperfomance}(Sigma) = \begin{pmatrix} 0.38*(Sigma)-0.71 & 1.87 \leq Sigma \leq 4.5 \\ 1 & Sigma > 4.5 \end{pmatrix},$$

$$\rightarrow p_{employeeperfomance}(3.48) = 0.38*(3.48)-0.71 = 0.61. \qquad (36)$$

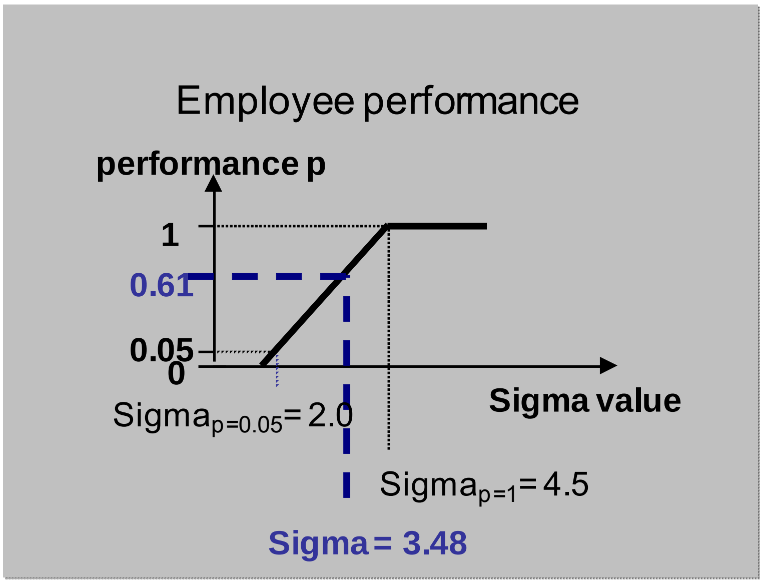

Fig. 9: Evaluation function for the performance measure “employee performance”

2.5. Consolidation of performance measure and process performance calculation

The last step of the concept is to consolidate the performance measures. A common method is to calculate the arithmetical mean (Magnusson et al., 2001, 226). Prerequisite for the calculation of the arithmetical mean is that performance measures do not influence one another (Berrah et al., 2004, 4280; Schrank, 2002, 175). In most of the cases the measures are not independent but they interact with each other (Clivillé et al., 2006, 1057). To consider the interaction between two measures, the two-additive fuzzy choquet integral is used, as stated below (Berrah et al., 2004, 4286).

$$TP(p_1, p_2, p_3, \ldots, p_n) = \sum_{i=1}^{n} p_i (w_i - \frac{1}{2}\sum_{j \neq 1} |I_{ij}|) + \sum_{I_{ij}>0} \min(p_i, p_j) I_{ij} +$$
$$\sum_{I_{ij}<0} \max(p_i, p_j) |I_{ij}|,$$

$$(w_i - \frac{1}{2}\sum_{i \neq j} |I_{ij}|) \geq 0. \qquad (37)$$

The parameter p_i describes the performance of the measure. The weights of the measures are given with w_i. The parameter I_{ij} describes the interaction between two performance measures and is defined in the range [-1, 1]. The interaction parameter is defined by experienced decision makers. A positive interaction parameter implies that performances of two measures p_i und p_j have, only together, a significant effect of the total process performance. A negative interaction parameter means that only one of two performance values is sufficient to have an effect of the total process performance. There is no interaction between the measures, if the interaction parameter is zero. The interaction parameter serves to provide fine adjustment of the weights of performance measures.

The following example illustrates the two-additive fuzzy choquet integral.

The decision makers want to consolidate the performance measures “employee performance” and “waiting time”:

- Calculated performance values:

$$p_{employeeperformance}(sigma) = 0.61$$
$$p_{waitingtime}(sigma) = 0.53$$

- Calculated weights:

$$w_{employeeperformance} = 0.56$$
$$w_{waitingtime} = 0.44$$

- Defined interaction parameter:

$$0.3$$

The interaction parameter of 0.3 represents that a good performance value of waiting time has no significant impact on the total performance value if the value of employee performance is bad and vice versa.

The constraint $(w_i - \frac{1}{2}\sum_{i \neq j} |I_{ij}|) \geq 0$ of (37) is fulfilled:

Employee performance:

$$(w_i - \frac{1}{2}\sum_{i \neq j} |I_{ij}|) \geq 0 \rightarrow (0.56 - \frac{1}{2} * 0.3) = 0.41 \geq 0. \qquad (38)$$

Waiting time:

$$(w_i - \frac{1}{2}\sum_{i \neq j} |I_{ij}|) \geq 0 \rightarrow (0.44 - \frac{1}{2} * 0.3) = 0.29 \geq 0. \tag{39}$$

Calculation of the total process performance value with (37):

$$\begin{aligned} &TP(p_1, p_2) = \sum_{i=1}^{2} p_i (w_i - \frac{1}{2}\sum_{j \neq 1} |I_{ij}|) + \sum_{I_{ij}>0} \min(p_i, p_j) I_{ij} + \sum_{I_{ij}<0} \max(p_i, p_j) |I_{ij}|, \\ &TP(0.53, 0.61) = 0.53 * (0.44 - \frac{1}{2} * 0.3) + 0.61 * 0.41 \\ &+ \min(0.53, 0.61) * 0.3 = 0.15 + 0.25 + 0.53 * 0.3 \approx 0.56 \end{aligned} \tag{40}$$

The total process performance is about 0.56 of 1.

3. Conclusions

This paper has introduced a conceptual model based on the fuzzy set theory to measure and evaluate service processes, which was subdivided into five parts. The first part was about the visualization of service processes by using the extended Service Blueprinting. In the next phase the performance measurements were determined with the aid of the CTC-CTQ-Driver-Tree. In the third phase the weights of the performance measures were defined with the aid of Fuzzy AHP to consider human perception. The fourth phase was about the measurement evaluation of the performance measures. Here a new evaluation function was used as well as the approach of *Chen* [6]. In the last phase the two-additive fuzzy choquet integral was introduced to consolidate performance measures. The main advantage of the two-additive fuzzy choquet integral is its consideration of interaction between two performance measures. The presented measurement and evaluation concept highlighted the advantages of using the fuzzy set theory in the context of measuring and evaluation of service processes. Nevertheless there are also some critical points, which have to be mentioned:

- Need for expertise:

  The definition of membership functions for the evaluation of performance measures requires expertise about the theory of fuzzy sets. Therefore it is necessary to train the decision makers in all areas of the fuzzy set theory. Decision makers have to understand the advantages of using fuzzy sets in the context of a measurement and evaluation procedure.

- The consideration of interaction between more than two performance measures is not possible:

  The two-additive fuzzy choquet integral only considers the interaction between two performance measures. In real situations it is possible to have interaction between more than two performance measures. The conception of a consolidation method, which takes the interaction of multiple performance measures into account, can be viewed as a further field of research.

- High calculation effort:

The use of fuzzy sets in the context of the presented concept produces a high calculation effort in contrast to common measurement and evaluation concepts. For example the effort to calculate the comparison grades rises more than proportionally with increasing numbers of performance measures. To counteract the high calculation effort the presented concept has to be transcribed as a computer-assisted solution.

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5. Authors

Author(s):

Schafiq Amini, Dipl.-Ing. ; Roland Jochem, Univ.-Prof. Dr.-Ing.
Technische Universität Berlin
Department of Quality Science
Pascalstr. 8-9, 10587 Berlin
schafiq.amini@tu-berlin.de ; roland.jochem@tu-berlin.de