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Integrating Quality Function Deployment with Fuzzy Cognitive Maps for Resolving Correlation Issues in the Roof Matrix

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ABSTRACT

The roof matrix represents correlations among engineering characteristics (EC) in the house of quality (HoQ) in Quality Functions Deployment (QFD). Correlations are usually measured qualitatively and omitted in the analysis. However, ignoring them may cause duplication of effort, decreased product performance, and unsatisfied customer requirements (CR). Hence, this paper intends to propose an approach to considering the correlations quantitatively. Fuzzy Cognitive Maps (FCM) were used for this purpose. Additionally, Axiomatic Design (AD), for examining relationships between CRs and ECs, and Fuzzy Analytic Hierarchy Process (FAHP) with the Extent Analysis (EA) were used for checking the consistency of the evaluations. The proposed approach was applied in a sheet metal die-making company for ranking CRs and ECs. Results show that FCM enables analysing the quantitative roof matrix practically. The square roof matrix that supports FCM's adjacency matrix structure successfully represents asymmetric relationships among ECs. Integrating the correlations into the analysis resulted in a change in the final ranking. It also helped determine the most manageable ECs, better satisfiable CRs, and most critical/least manageable ECs.

Key Words: Quality Function Deployment; Fuzzy Cognitive Maps; Asymmetric Square Roof Matrix; Independence Axiom; Fuzzy Analytic Hierarchy Process; Extent Analysis.

JEL Classification Codes: C61, M11, L15

1. INTRODUCTION

Quality Function Deployment (QFD) is one of the well-known customer-oriented methodologies. It provides a conceptual map for cross-functional planning and communication applications. It is used for exploring real-world situations where human preference is involved in the decision-making process. However, decision-makers' logic and subjectivity play a crucial role in that process. Hence, such an environment may require fuzzy logic to make realistic decisions. QFD methodology does address such fuzziness at some level, but it becomes more effective and provides more realistic results with fuzzy logic (Upadhyay, Hans Raj, & Dwivedi, 2012). Some other issues regarding QFD are couplings, correlations and the roof matrix type. Couplings are relationships between customer requirements (CR) and engineering characteristics (EC). According to Manchulenko (2001), only %5-10 of companies use QFD continuously because of the long development time and cost resulting from the couplings. Contrarily, correlations are interrelationships among ECs. According to Özgener (2003), strong positive correlations between ECs may result in duplication of effort. On the other hand, negative correlations may adversely affect the product's performance because the improvement of one EC acts against the others. Hence managing negative and positive correlations is crucial. However, to the best of our knowledge, there are not many studies regarding the management of the correlation effect. Finally, the widely used type of roof matrix is the triangle roof matrix that supports symmetric relationships among ECs. However, an asymmetric square matrix is more suitable because interdependencies among ECs are asymmetric so one-way in real-life. While one EC is the source of the effect, the other one receives the effect. The roles of these two ECs as being a source or receiver may change in their relationship with other ECs. Also, the existence and strength of the relationship differ depending on CRs.

For all above considerations, this paper is set out to structure a correlation management model in QFD. For this purpose, square roof matrix and Fuzzy Cognitive Maps (FCM) was used as they allow determining and

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visualising all kinds of casual asymmetric relationships among ECs. Additionally, the Independence Axiom (IA) of Axiomatic Design (AD) was employed to reduce the CR-EC coupling effect. The proposed methodology was applied to a die making company in the automotive industry. A team of experts and customers from the subject company participated in the application process. Hence, the Fuzzy Analytic Hierarchy Process (FAHP) with the Extent Analysis (EA) was also applied to obtain consistent evaluations.

The study presented in this paper is one of the first investigations to utilize FCM for resolving correlation issues among ECs by quantizing correlation values and examining cyclic and acyclic networks among ECs. This paper also provides an EC classification/management approach by using centrality and casualty values of ECs that are major FCM outputs.

The remaining part of the paper proceeds as follows: The second section reviews the literature, the third section concerns correlation issues, the fourth section provides brief information about the methodologies employed, the fifth section explains the proposed model with a real-life application, and the sixth section presents and discusses the results.

The terms “EC-EC interrelationships” and “correlations” are used interchangeably in this paper.

2. LITERATURE REVIEW

There have been a variety of applications with different focus areas of QFD methodology, such as (i) selecting strategic maintenance techniques (Baidya, Kumar Dey, Kumar Ghosh, & Petridis, 2018) and heating systems (Ozdemir, Alcan, Basligil, & Cakrak, 2018) by employing QFD with AHP, (ii) rating/prioritizing ECs with QFD and technique for order preference by similarity to an ideal solution under fuzzy environment (Wang, Yan, Wang, & Yu, 2020), and also with z-numbers, QFD and evaluation based on distance from average solution methods (Mao, Liu, Mou, & Liu, 2021), (iii) determining weights for team members and CRs by utilizing QFD with z-numbers (Song, Wang, & Li, 2020), (iv) for assessing risk in mining sector by using QFD with AHP and fuzzy inference system (Cinar & Cebi, 2020), analysing supply chain resilience in freight forwarding with QFD and two-step house of quality (HoQ) design (Isti’anah, Praharsi, Maharani, & Wee, 2021), (v) determining supplier evaluation criteria and final set of suppliers accordingly by using QFD with interval data envelopment analysis (Bao & Li, 2021).

The literature about QFD integrated with AD applications is new and limited compared to other study areas of QFD. Cauchick Miguel, Carnevalli and Calarge (2007) proposed an AD-based QFD model. The aim was overcoming difficulties in determining CRs, translating them into FRs and resolving dependencies between them. The authors focused on only IA of AD. Carnevalli, Miguel and Calarge (2010) proposed a theoretical and conceptual model of QFD. They aimed to minimize usage difficulties of QFD, such as interpreting the voice of customer (VoC), defining and prioritizing quality characteristics and working with large matrices. However, they did not tested the proposed model in a real-life problem. Arsenyan and Büyüközkan (2016) combined QFD, AD and a fuzzy rule-based system. The integrated methodology was applied to a technology planning problem of a textile company. Lapinskienė & Motuzienė (2021) combined QFD and AD with Complex Proportional Assessment of Alternatives (COPRAS) in a building design problem. The authors both utilized independence and information axioms of AD to achieve independence and calculate the success probability of the solutions to be used as input in COPRAS. Orbak, Korkmaz, & Aydın (2021) employed QFD with AD in selecting a suitable intercity bus seat design with considering commuters’ specifications and corresponding technical requirements. For a brief literature review about QFD and AD, please refer to Fauzi Malik, Napitupulu, & Ginting (2020).

The literature about considering the correlation matrix by quantifying its impacts is also very minimal (Chan & Wu, 2002). Tseng and Torng (2011) presented a methodology based on the partitioning and tearing algorithm of the design structure matrix. The proposed approach dealt with the weakness of correlations among ECs that were mostly ignored but affected the implementation sequence of the project tasks and resulted in delays or queuing in product design/project development. Li et al. (2012) used rough sets for estimating correlations. Their approach introduces a category factor for a correlation to determine the effects of the correlation categories on the related measures. According to the authors, this approach was effective in using the knowledge of the QFD team and accomplishing decision-making in the new product development process (Li et al., 2012). Bencherif, Mouss and Benaicha (2013) proposed using the theory of inventive problem solving for resolving negative correlations among ECs. In this approach, negatively correlated ECs were replaced with positive ones. That may result in information loss in the correlation matrix. In the paper of Cavallini et al. (2013), information axiom was used for investigating negative correlations among ECs by applying the simple probability. However, their application conflicts with the nature of the IA, which is originally based on conditional probability. In the paper of Iqbal, Grigg, Govindaraju, & Campbell-Allen, (2015), Manhattan Distance Measure (MDM) was used for ranking ECs. In order to apply MDM, the authors used two hypothetic ideal and undesirable roof correlation matrices besides the given correlation matrix. The ideal matrix represented the perfect situation where all the correlations were strong positive (+1). The undesirable matrix represented the worst situation where all the correlations were strong negative (-1). Then Manhattan distance from the ideal matrix and undesirable matrix were calculated. The strength of each EC was calculated by dividing the former MDM value by the latter. This approach may be practical for considering all types of roof correlations in the rankings, but the term "ideal" may not be ideal for all types of EC correlations due to the correlation issues explained in Section 3. In another study, Fuzzy Analytic Network Process (F-ANP) and EA was used for determining the importance weights of ECs (Mistarihi, Okour, & Mumani, 2020). However, interrelationships among ECs were not evaluated regarding CRs. Finally, Fazeli & Peng (2021) adopted a broadly similar position with ours. They did not only attempt to quantify EC-EC correlations, but also investigated cause and effect relations, and interdependence and emphasised the importance of direct and indirect relationships between ECs. They employed decision- making trial and evaluation laboratory for this purpose. Moreover, the authors also highlighted the importance of using an appropriate roof matrix. According to them, with their terms, "a square-shaped non-symmetric matrices" suit better real-life design problems in which "unequal mutual interactions" exist. However, in their study, correlations were not evaluated/determined with respect to each CR and all evaluations were done under the assumptions of CRs were uncorrelated.

3. CORRELATION ISSUES AMONG ECs

Close attention must be paid to negative roof correlations because negatively correlated EC's conflict with each other. An improvement of one may worsen the other one. They require special planning or breakthrough attempts since they represent bottlenecks in product design (Li, Tang, & Luo, 2010) and adversely affect the performance of the product (Bencherif et al., 2013; Iqbal et al., 2015). On the other hand, positive correlations indicate that ECs are mutually supportive. An improvement in one results in an improvement on the other at least to some extent. However, high positive correlations among ECs, which is defined as "ideal correlation" by Iqbal et al. (2015), may cause undesirable results. For example, increased alloy content of steel provides better hardness. However, too much increase in the alloy content and so hardness makes the material fragile. Moreover, strong positive or even any positive roof correlations may cause duplication of effort (Özgener, 2003) by magnifying the relationship. Assume that there are four ECs. EC_2, EC_3 and EC_4 affect EC_1, and EC_3 affects EC_4. If EC_3 is improved, both EC_1 and EC_4 directly and simultaneously get affected. Additionally, EC_1 is being indirectly affected by the path of EC_3 - EC_4 - EC_1. Because of that simultaneous improvements, it is desired to have correlation values zero or close to zero. It is crucial to have a network that does not constitute a cycle (acyclic network) in the roof matrix. In other words, a desirable roof matrix is a diagonal matrix where each EC is independent of each other. Independence is also essential for resource allocation to the subject QFD project/product (Tseng & Torng, 2011). For example, if there is a subset of ECs that are not correlated with the rest, it is advisable, easier, and manageable to implement the tasks related to that particular subset of ECs firstly. Because any change in these ECs will not affect the others. If there are interdependencies between ECs, tasks affect each other, and more information is required to achieve the best design. Consequently, both the positive and negative correlations in the roof matrix are not desired. A method that considers all types of correlations is necessary to use for analysing the roof of HoQ.

In many studies, the EC correlation matrix is assumed as symmetric, and triangular roof matrix is used. However, interdependencies among ECs in real-life cases are not symmetric. What is more, their influence on each other varies depending on the CRs (Reich & Levy, 2004). In this vein, the asymmetric roof matrix was proposed by Moskowitz and Kim (1997), and improved by Reich and Levy (2004). Reich and Paz (2008) explained the necessity of using an asymmetric square roof matrix with a cellular phone design problem. The battery size (EC_1) has a strong positive effect on the usage time between charges (EC_2) regarding the use of a cellular phone for a long time (CR_1). On the contrary, usage time between charges (EC_2) does not affect the battery size (EC_1). Therefore, there is a one-way effect between EC1- EC_2. Additionally, if that correlation is investigated for having a user-friendly interface (CR_2), it is evident that there is none correlation between EC_1- EC_2.

For all the reasons explained above, the FCM method may be a solution to holistically examining the roof matrix of HoQ as it naturally supports the asymmetric relationship between ECs. To the best of our knowledge, FCM has not been applied to QFD.

4. PRELIMINARIES

4.1.Fuzziness and Fuzzy Numbers

As stated in section 1, fuzzy logic was used throughout this study as it captures the subjectivity of decision-makers effectively and provides realistic results. Lotfi A. Zadeh introduced the ordinary fuzzy sets theory in 1965 (Zadeh, 1965). It was based on the rationality of uncertainty due to imprecision or vagueness. It is a practical way to represent vague knowledge and linguistic variables and, therefore, widely applied to solve real-life problems that are usually subjective, vague, and imprecise. A fuzzy set is characterized by a membership function $\mu(x)$ that defines a membership value between [0, 1] for each point in the input space. While 0 and 1 indicate the minimum and maximum degree of memberships respectively, all the intermediate values indicate degrees of partial memberships (Sanayei, Farid Mousavi, & Yazdankhah, 2010). There are various kinds of fuzzy numbers used in membership functions such as triangle, trapezoid, and the bell curve. However, the use of triangular functions is relatively common in the literature (Karsak, 2004) as they can be managed easily from the computational point of view. A triangular fuzzy number can be represented merely as (l, md, h). These parameters denote the smallest possible, the most promising, and the largest possible values that describe a fuzzy event. In linguistic variables of view, various types of relations (fuzzy scales) can be used. For example, five different relations can be denoted as very low (VL), low (L), medium (M), high (H) and very high (VH). There are also fuzzy scales of which linguistic variables are in [-1; 1].

Since the development of ordinal fuzzy sets, several extensions of it have been introduced, such as Type-2, interval-valued, intuitionistic, nonstationary, hesitant, pythagorean, spherical, and interval-valued spherical fuzzy sets (SFS), fuzzy multisets, and neutrosophic sets (Kutlu Gündoğdu & Kahraman, 2020). The lately developed of them are hesitant and SFS. Hesitant fuzzy sets proposed by Torra (2010) consider uncertain/ hesitant judgements of decision-makers. In this method, contrary to using pre-determined membership functions they are determined/calculated by aggregating potential membership functions belongs to decision-makers into one. SFS developed by (Kutlu Gündoğdu & Kahraman, 2019) are a synthesis of pythagorean and neutrosophic fuzzy sets. In SFS, membership functions are determined with the squared sum of membership, non-membership and hesitancy/indeterminacy parameters. Finally, different from single valued SFS, an interval with upper and lower degrees for the parameters are set and considered in interval-valued SFS developed by (Duleba, Kutlu Gündoğdu, & Moslem, 2021).

We preferred using ordinary fuzzy sets of Saaty throughout the study as our focal point is resolving correlation issues in the roof matrix. Also, it would be better employing recently developed fuzzy sets in case of having large groups of decision makers where indeterminacy/hesitancy is high. In our study, we have worked with a small group of decision-makers.

4.2. Axiomatic Design

IA of AD was used for the purpose of achieving a product design of that FRs and DPs, which correspond to CRs and ECs in QFD, are independent of each other. What is more, the base of IA and CR-EC matrix of QFD perfectly matches each other as both aim resolving dependence issues between CRs and ECs. Hence it is particularly useful and proper for examining CR-EC relationship. AD is a structured and rational method for improving design activities in four stages: Customer domain (customer needs), functional domain (FRs that satisfy customer needs), physical domain (PhD- design parameters that satisfy FRs) and process domain (process variables that resolve each FR). Each domain is related to each other and characterized by a set of information. The design process must be developed in a top-down manner. It should start with obtaining information from customers and continue with PhD until the point where the design object is defined with sufficient detail, and no decomposition can be done. This process is called hierarchical decomposition and zigzagging (Park, 2007). Its objective is to decompose both the FRs and the DPs for further detailing before manufacturing the product (El-Haik & Wasiloff, 2004). It shows the designing hierarchy of an object and makes designing a much more controllable process (El-Haik & Wasiloff, 2004; Goncalves-Coelho, Mourao, & Pereira, 2005). Therefore, it is obvious that QFD and AD has a similar base on behalf of design domains. AD uses independence and information axioms for improving the design. All FRs should be independent of any other, and the information content of design should be minimum. Therefore, the AD may be a key to describe (Liu, 2011) and calculate the independence level of the relationship matrix (Çebi & Kahraman, 2011) In this study, only IA was used.

According to IA, there are three design types; uncoupled, decoupled, and coupled. The uncoupled designs are ideal designs since they have a diagonal matrix that provides none relationships between FRs and DPs (between CRs and ECs). Therefore, the design complexity of the product is low, and costs and other constraints related to the design are manageable. If the matrix is triangular, the design is decoupled and acceptable. All other types of matrix are accepted as coupled and should be avoided. If there are fewer DPs than FRs, the design is assumed to be coupled and should be avoided. In the reverse situation, the design is accepted as either coupled or redundant. In this case, only redundant designs are acceptable if they are uncoupled or decoupled (El-Haik & Wasiloff, 2004; Goncalves-Coelho et al., 2005).

4.3.Analytic Hierarchy Process

It is hard to define the best choice as the human mind is incapable of evaluating all alternatives on a set of criteria. AHP is one of the most common, practical, easily applicable and powerful decision-making methodologies for determining priority rankings of criteria originally developed by Saaty (Saaty, 1986, 1994). Hence, in this study, fuzzy version of the AHP was utilized for obtaining consistent judgements from decision-makers. It is such a method that is based on a stepwise comparison of alternatives regarding two criteria for determining the best option (Abastante & Lami, 2012). It enables decision-makers to determine overall rankings of the alternatives. It provides a consistency rate to measure the consistency of judgment of decision-makers (Kordi, 2008; Srichetta & Thurachon, 2012). It consists of five steps (Srichetta & Thurachon, 2012). In the first step, criteria and sub-criteria are determined, and hierarchically arranged into a tree-like diagram of which top level represents the goal of the decision problem. In the second step, decision-makers assess the relative importance of each criterion by using a (1-9) scale defined by Saaty. In the third step, the average weight for each normalized criterion is calculated. In the fourth step, a pairwise comparison matrix is obtained. Finally, the overall score for each alternative is calculated. To date, there are different scales used in AHP, namely linear, which is the original one proposed by Saaty, power, geometric, logarithmic, root square, asymptotical, inverse linear and balanced (as cited in Ishizaka, 2019). We preferred using the linear scale of Saaty as our focal point is resolving correlation issues in the roof matrix.

4.4. Fuzzy Cognitive Maps

FCM method was used in the roof of the HoQ. The significant advantages of using FCM are that it allows us to quantify EC-EC relationships, process negative, positive and zero correlations, and investigate whether there is a network of interdependencies among ECs (which is the existence of a cyclic network). Also, it is particularly is practical, easily applicable and interpretable. It enables the examiner to describe the complex interactions between the factors of a problem (Christoforou & Andreou, 2017). They are based on the experience and knowledge of the experts; describe the behaviour of the system symbolically, and illustrate the system by a directed graph. Developing an FCM consists of three steps. Firstly, experts determine the essential factors affecting the behaviour of the system. Secondly, they decide each concept representing the factors. Finally, they determine and quantify the interrelationships between the concepts. For the last step, it is advised to have a single map for each expert firstly, and aggregate all into one map secondly. In that way, each expert transforms his/her knowledge on a map (Groumpos, 2010) without being affected by each other.

FCMs are a combination of neural networks, graph theory, fuzzy logic, semantic networks, and expert systems. The fundamental unit of a map is the concept, which is a variable and represented by a node. There are two types of variables, which are casual (driver) and effect variables (receiver). Relationships/interconnections between them are represented with fuzzy weighted arcs. For example, if C_1 affects C_2, they are called casual and effect variable respectively. The origin of the arrow is at C_1, and it terminates at C_2(Groumpos, 2010). Arc values vary in the interval of [-1,1] (Groumpos, 2010; Papageorgiou, 2012).

5. PROPOSED MODEL and APPLICATION

The structure of the model proposed in this study is as follows: IA is used for examining if CR-EC relationship matrix was coupled or decoupled. Then the EA is used for computing the relative weights of the customer requirements, but before that, FAHP is used for checking the consistency of the customers. Afterward, the FCM method is used for quantitatively analysing the asymmetric EC-EC relationships. Finally, the importance rankings of the CRs are obtained by computing the importance rankings of their corresponding ECs. The steps of the proposed model are as in Fig. 1. It was practiced in a company that produces sheet metal dies for the automotive industry.

Step 1. Team formation. Project scope and priorities are defined and communicated to other departments to prevent questions about the team and to encourage team members to dedicate their time accordingly. In product design, teams are generally composed of experts from marketing, design, quality, finance, and production departments. On the contrary, in product improvements, teams are small as the QFD process will only need to be modified (Besterfield et al., 2011).

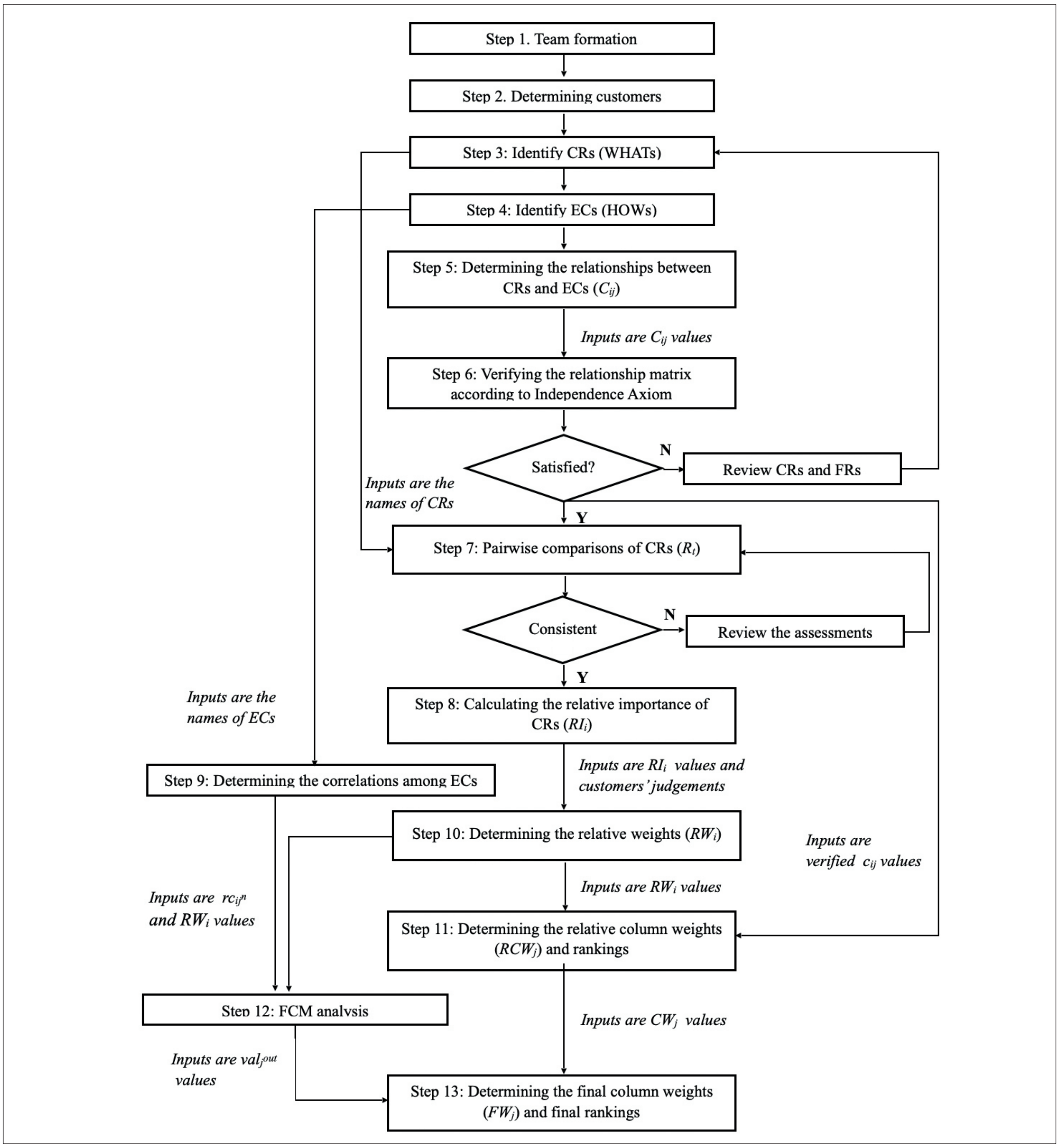

Fig. 1: Steps of the Proposed Model

Application: *The team of experts consisted of a plant manager and technical manager from the subject company, and a deputy technical manager of another sheet metal die company. Each had 10-15 years of experience. Their assessments were weighted equally since their length and area of experience is the same.*

Step 2. Determining customers. According to Mazur (1997), determining which customers to be involved in the QFD process depends on the diversity of the market, product complexity and use, and sophistication of customers as cited in Erkarslan and Yılmaz (2011). If QFD practice is done for an existing product, current customers should be the primary source of information. Otherwise, potential customers should be the main source of information.

Application: *The top ten customers, seven of which were from Europe and the rest were from the local market, were chosen regarding their shares in the capacity.*

Step 3. Identifying CRs (WHATs). Once customers to contact are decided, CRs are collected (van Aartsengel & Kurtoğlu, 2013). Then they are placed on the left side of the HoQ as $CR_1, CR_2, \ldots, CR_k$ where k is the number of the CRs.

Application: *CRs were identified by examining the past orders and customer service feedback data: Repeatability, visual quality of stamped parts (trimming burrs, material thinning, wrinkles), high production speed, easy accessibility of standard components in sheet metal dies, long lifetime* *of tool steels used for trimming and cold forming, ease of replacement and conformity of design data with the sheet metal die. Please refer to appendix for more information about CRs.*

Step 4: Identifying ECs (HOWs). In this step, raw CRs are transformed into ECs that will represent technical attributes by the expert team. Then, they are placed above the relationship matrices of HoQ as $EC_1, EC_2, \ldots, EC_m$ where mn is the number of the EC's.

Application: *The corresponding ECs were determined: Repeatability of CNC machines, visual quality parameters of stamped parts (cutting clearance, the surface roughness of the tool steels, blank holder pressure/force), strokes per minute (spm), the ratio of standardized elements, the hardness of tool steels, replacement time and the number of software. Please refer to appendix for more information about ECs.*

Step 5. Determining CR - EC relationships. The experts determine the effect of ECs on CRs based on their experience by using a linguistic scale. Then linguistic matrices of the experts are converted into a fuzzy matrix, and aggregated into one with Eq. (1) where n denotes the number of experts, C_{ijn} denotes the fuzzy relationship between i^{th} CR and j^{th} EC estimated by the n^{th} expert, and $C_{ij} = \left(C_{ij}{}^{l}, C_{ij}{}^{md}, C_{ij}{}^{h}\right)$ represents an aggregated relationship evaluation matrix of the experts.

$$C_{ij} = \frac{1}{\mathrm{n}} \otimes \left(c_{ij1} \oplus c_{ij2} \oplus \ldots \oplus c_{ijn}\right) \tag{1}$$

$i = 1, \ldots, k$ $j = 1, \ldots, m$ and $n = 1, \ldots, e$

Application: *Three evaluation matrices were obtained from the experts. They used a five-level linguistic scale: Very low (VL) (0, 0.1, 0.2), low (L) (0.2, 0.3, 0.4), medium (M) (0.4, 0.5, 0.6), high (H) (0.6, 0.7, 0.8) and very high (VH) (0.8, 0.9, 1). Then the matrices were fuzzified and aggregated into one with Eq. (1) as in Fig. 2. A brief numerical depiction is given below.*

While C_{11} denotes the aggregated fuzzy relationship between CR$_1$-EC$_1$, $C_{11} = \frac{1}{3} \otimes \left(c_{111} \oplus c_{112} \oplus c_{113}\right) = \frac{1}{3} \otimes \left[(0.8, 0.9, 1.0) \oplus (0.6, 0.7, 0.8) \oplus (0.6, 0.7, 0.8)\right] = (0.66, 0.76, 0.86)$

Step 6. Verifying EC-CR relationships according to IA. In the conventional AD, relationships are symbolized by 0 (absence of the relation) or 1 (presence of the relation) therefore, a design with a weak relationship is considered as a coupled design (Çebi & Kahraman, 2011). It cause a loss in VoC during the process of redefining CRs until an uncoupled design is achieved. However, it should be acceptable even it is categorized as coupled. A fuzzy dependency coefficient $\widetilde{\boldsymbol{C}}$ can prevent rejecting such designs. Where C_{ij} is the fuzzy relationship between the each CR_i and EC_J, $\widetilde{\boldsymbol{C}}$ is calculated with Eq. (2).

$$\widetilde{\boldsymbol{C}} = \frac{\sum_{i=1}^{k-1} \sum_{j=i+1}^{k} C_{ij}}{\sum_{i=1}^{k} \sum_{j=i+1}^{k} 1} \tag{2}$$

To decide whether a coupled design is in the limits of acceptable tolerance, $\widetilde{\boldsymbol{C}}$ is compared with a tolerance level γ. The tolerance level is firstly defined by Suh (1990). It can have any value based on the nature, time, and budget of the QFD project and experts' opinions. If 0<($\widetilde{\boldsymbol{C}}$) **≤γ**, the design is assumed to be decoupled, the relationship matrix satisfies IA; couplings are negligible, and time and cost effects of couplings are in acceptable limits. If ($\widetilde{\boldsymbol{C}}$) **>γ**, the matrix is coupled, IA is not satisfied, the couplings will have harmful effects on QFD results, and they have to be eliminated until the dependency coefficient value is below **γ**. The coupled matrix is manipulated by changing the order of CRs and corresponding ECs. Couplings can be eliminated or minimized to an acceptable level by the reordering algorithm defined by Çebi and Kahraman (2010): The sequence of CRs and ECs are determined by Eq. (3-4) where C_{ij}^{md} is the middle value of a fuzzy triangular number, which represents $CR_i - EC_J$ relationships, SCR_i and SEC_J are the sequence scores of CR_i and EC_J, respectively. Then, CRs are ranked regarding to their SCR_i values from minimum to maximum in the matrix.

$$SCR_i = \sum_{j=1}^{m} C_{ij}^{md} \tag{3}$$

$$SEC_J = \sum_{i=1}^{k} C_{ij}^{md} \tag{4}$$

Application: *Where C_{1j} is the fuzzy relationship between CR_1 and all $EC_J s$,* $\sum_{j=i+1}^{k} C_{1j} = C_{1(21)} \oplus C_{1(22)} \oplus C_{1(23)} \oplus C_{13} \oplus C_{14} \oplus C_{15} \oplus C_{16} \oplus C_{17} =$

$= (0.67, 0.77, 0.87) \oplus \ldots \oplus (0.13, 0.23, 0.33) = (1.80, 2.20, 2.60).$

Likewise, all calculations were done for each CR. Then, calculated values were summed up to obtain

$\sum_{i=1}^{k-1} \sum_{j=i+1}^{k} C_{ij} = \sum_{j=i+1}^{k} C_{1j} \oplus \sum_{j=i+1}^{k} C_{(21)j} \oplus \sum_{j=i+1}^{k} C_{(22)j} \oplus$

$\oplus \sum_{j=i+1}^{k} C_{(23)j} \oplus \sum_{j=i+1}^{k} C_{3j} \oplus \sum_{j=i+1}^{k} C_{4j} \oplus \sum_{j=i+1}^{k} C_{5j} \oplus$

$\sum_{j=i+1}^{k} C_{6j} \oplus \sum_{j=i+1}^{k} C_{7j} = (1.80, 2.20, 2.60) \oplus$

$\ldots \oplus (0.00, 0.00, 0.00) = (5.13, 6.33, 7.53).$

Hence $\widetilde{\boldsymbol{C}} = \frac{\sum_{i=1}^{k-1} \sum_{j=i+1}^{k} C_{ij}}{\sum_{i=1}^{k} \sum_{j=i+1}^{k} 1} = (0.14, 0.18, 0.21)$, *which is greater than γ=which is greater than (0.1,0.1,0.1) which was set by the experts. Hence, CRs and ECs were re-ranked following to the reordering algorithm as explained below.*

	EC_1			EC_{21}			EC_{22}			EC_{23}			EC_3			EC_4			EC_5			EC_6			EC_7		
CR_1	0.66	0.76	0.86	0.66	0.76	0.86	0.4	0.5	0.6	0	0	0	0	0	0	0	0	0	0.6	0.7	0.8	0	0	0	0.13	0.23	0.33
CR_{21}	0.4	0.5	0.6	0.73	0.83	0.93	0.4	0.5	0.6	0	0	0	0	0	0	0	0	0	0.53	0.63	0.73	0	0	0	0	0	0
CR_{22}	0.46	0.56	0.66	0.66	0.76	0.86	0.66	0.76	0.86	0.4	0.5	0.6	0.73	0.83	0.93	0	0	0	0.26	0.36	0.46	0	0	0	0	0	0
CR_{23}	0.46	0.56	0.66	0.6	0.7	0.8	0	0	0	0.73	0.83	0.93	0.4	0.5	0.6	0	0	0	0.26	0.36	0.46	0	0	0	0	0	0
CR_3	0	0	0	0	0	0	0	0	0	0	0	0	0.73	0.83	0.93	0	0	0	0	0	0	0	0	0	0	0	0
CR_4	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0.66	0.76	0.86	0	0	0	0.33	0.43	0.53	0	0	0
CR_5	0	0	0	0.06	0.16	0.26	0	0	0	0	0	0	0.46	0.56	0.66	0	0	0	0.8	0.9	1	0	0	0	0	0	0
CR_6	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0.26	0.36	0.46	0	0	0	0.66	0.76	0.86	0	0	0
CR_7	0.53	0.63	0.73	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0.66	0.76	0.86

Fig. 2: Fuzzy Aggregated EC-CR Relationships Matrices of the Team

Table 1: Triangular Fuzzy Conversion Scale

Linguistic variables	Crisp scale	Fuzzy scale	
		Fuzzy values	Reciprocal values
Equally preferred (EQP)	1	(1, 1, 1)	(1, 1, 1)
Equally to moderately preferred (EQ-MP)	2	(1, 2, 3)	(1/3, 1/2, 1)
Moderately preferred (MP)	3	(2, 3, 4)	(1/4, 1/3, 1/2)
Moderately to strongly preferred (M-SP)	4	(3, 4, 5)	(1/5, 1/4, 1/3)
Strongly preferred (SP)	5	(4, 5, 6)	(1/6, 1/5, 1/4)
Strongly to very strongly preferred (S-VSP) preferred	6	(5, 6, 7)	(1/7, 1/6, 1/5)
Very strongly preferred (VSP)	7	(6, 7, 8)	(1/8, 1/7, 1/6)
Very strongly to extremely preferred (VS-EXP)	8	(7, 8, 9)	(1/9, 1/8, 1/7)
Extremely preferred (EXP)	9	(8, 9, 9)	(1/9, 1/9, 1/8)

While SCR_1 *denotes the sequence score of* CR_1 $C_{1j}^{md}s$ *denote the middle values of the fuzzy triangular values of* CR_1 – EC_j *relationships,* $SCR_1 = C_{11}^{md} \oplus \ldots \oplus C_{17}^{md} = 0.77 \oplus \ldots \oplus 0.23 = 2.96$.

Likewise, all calculations were done for each CR. Then obtained SCR values were examined to determine the new order, $SCR_i = 2.96, 2.46, 3.80, 2.96, 0.83, 1.20, 1.63, 1.13, 1.40$ *respectively. Hence, the new order, which provided a* $\tilde{C}$=(0.06, 0.07, 0.09) *smaller than γ, became* $CR_3 < CR_6 < CR_4 < CR_7 < CR_5 < CR_{21} < CR_3 < CR_{23} < CR_{22}$. *Finally, CR-EC relationship matrix given in Fig. 2 was updated according to the new ranking and placed in the HoQ in Fig. 8.*

Step 7. Pairwise comparisons of CRs. In this step, customers make pairwise comparisons of CRs, and their consistency is checked. A nine-point linguistic scale is used for the comparison, as in Table 1. Afterward, linguistic comparisons are translated into fuzzy triangular numbers. Where $= (r_{ijt}^{l}, r_{ijt}^{md}, r_{ijt}^{h})$ denotes a pairwise fuzzy comparison value between the element i and j of the customer t, and R_t denotes the pairwise comparison matrix of the customer t can be represented as $R_t = \begin{bmatrix} (1,1,1) & \cdots & r_{1kt} \\ \vdots & \ddots & \vdots \\ r_{k1t} & \cdots & (1,1,1) \end{bmatrix}$ where i *and* $j = 1, \ldots, k$ *and* $t = 1, \ldots, s$.

AHP outcomes crucially depend on the consistency of pairwise comparisons made by decision-makers. It is necessary to check the consistency of all R_t matrices because the fuzzy extent value RI_i will be obtained in step 8, will be dubious if R_t's are inconsistent, where consistency ratio bigger than 0.1. In this case, the customer that has inconsistent comparisons should review and revise his/her judgments until the consistency ratio is below 0.1. Kwong and Bai (2003) proposed to defuzzfy R_t matrices with Eq. (5) before calculating the consistency index CI with Eq. (6) and consistency ratio CR with Eq. (7).

$$r_{ijt} = \frac{\left(r_{ijt}^{l} + 4r_{ijt}^{md} + r_{ijt}^{u}\right)}{6} \qquad (5)$$

$$CI = \frac{\lambda_t - d}{d - 1} \qquad (6)$$

$$CR = \frac{CI}{RI(d)} \qquad (7)$$

Where λ_t is the largest eigenvalue of R_t, d is the dimension of the matrix and $RI(d)$ is a random index depending on d, Table 2.

Table 2: $RI(n)$

d	3	4	5	6	7	8	9
$RI(d)$	0.58	0.9	1.12	1.24	1.32	1.41	1.45

Application: *A multi-level AHP tree was designed for checking the consistency as CR_2 had sub criteria. Customers used the FAHP scale given in Table 1 for the linguistic comparisons. Evaluation matrices of Customer 1 of which* $\lambda_{max} = 7.269, CI = 0.045, CR = 0.034$ *for the main criteria,* $\lambda_{max} = 3.01$, $CI = 0.005$, $CR = 0.008$ *for the sub-criteria of CR_2 were given as an examples below.*

Linguistic matrix:

$$R_{1(main)} = \begin{bmatrix} EQP & SP & EQP & EXP & MP & EXP & SP \\ 1/SP & EQP & 1/MP & MP & EQP & VSP & EQP \\ EQP & MP & EQP & EXP & MP & EXP & SP \\ 1/EXP & 1/MP & 1/EXP & EQP & 1/SP & EQP & 1/MP \\ 1/MP & EQP & 1/MP & SP & EQP & EXP & MP \\ 1/EXP & 1/VSP & 1/EXP & EQP & 1/EXP & EQP & 1/MP \\ 1/SP & EQP & 1/SP & MP & 1/MP & MP & EQP \end{bmatrix} \quad R_{1(sub)} = \begin{bmatrix} EQP & EQP & \frac{1}{SP} \\ EQP & EQP & \frac{1}{SP} \\ SP & SP & EQP \end{bmatrix}$$

Fuzzy matrix:

$$R_{1(main)} =$$

$$\begin{bmatrix} 1.00,1.00,1.00 & 4.00,5.00,6.00 & 1.00,1.00,1.00 & 8.00,9.00,9.00 & 2.00,3.00,4.00 & 8.00,9.00,9.00 & 4.00,5.00,6.00 \\ 0.16,0.20,0.25 & 1.00,1.00,1.00 & 0.25,0.33,0.50 & 2.00,3.00,4.00 & 1.00,1.00,1.00 & 6.00,7.00,8.00 & 1.00,1.00,1.00 \\ 1.00,1.00,1.00 & 2.00,3.00,4.00 & 1.00,1.00,1.00 & 8.00,9.00,9.00 & 2.00,3.00,4.00 & 8.00,9.00,9.00 & 4.00,5.00,6.00 \\ 0.11,0.11,0.12 & 0.25,0.33,0.50 & 0.11,0.11,0.12 & 1.00,1.00,1.00 & 0.16,0.20,0.25 & 1.00,1.00,1.00 & 0.25,0.33,0.50 \\ 0.25,0.33,0.50 & 1.00,1.00,1.00 & 0.25,0.33,0.50 & 4.00,5.00,6.00 & 1.00,1.00,1.00 & 8.00,9.00,9.00 & 2.00,3.00,4.00 \\ 0.11,0.11,0.12 & 0.12,0.14,0.16 & 0.11,0.11,0.12 & 1.00,1.00,1.00 & 0.11,0.11,0.12 & 1.00,1.00,1.00 & 0.25,0.33,0.50 \\ 0.16,0.20,0.25 & 1.00,1.00,1.00 & 0.16,0.20,0.25 & 2.00,3.00,4.00 & 0.25,0.33,0.50 & 2.00,3.00,4.00 & 1.00,1.00,1.00 \end{bmatrix}$$

$$R_{1(sub)} = \begin{bmatrix} 1.00,1.00,1.00 & 1.00,1.00,1.00 & 0.16,0.20,0.25 \\ 1.00,1.00,1.00 & 1.00,1.00,1.00 & 0.16,0.20,0.25 \\ 4.00,5.00,6.00 & 4.00,5.00,6.00 & 1.00,1.00,1.00 \end{bmatrix}$$

Defuzzified matrix:

$$R_{1(main)} = \begin{bmatrix} 1.00 & 5.00 & 1.00 & 8.83 & 3.00 & 8.83 & 5.00 \\ 0.20 & 1.00 & 0.34 & 3.00 & 1.00 & 7.00 & 1.00 \\ 1.00 & 3.00 & 1.00 & 8.83 & 3.00 & 8.83 & 5.00 \\ 0.11 & 0.34 & 0.11 & 1.00 & 0.20 & 1.00 & 0.34 \\ 0.34 & 1.00 & 0.34 & 5.00 & 1.00 & 8.83 & 3.00 \\ 0.11 & 0.14 & 0.11 & 1.00 & 0.11 & 1.00 & 0.34 \\ 1.00 & 1.00 & 0.20 & 3.00 & 0.34 & 3.00 & 1.00 \end{bmatrix} \quad R_{1(sub)} = \begin{bmatrix} 1.00 & 1.00 & 0.20 \\ 1.00 & 1.00 & 0.20 \\ 5.00 & 5.00 & 1.00 \end{bmatrix}$$

Finally, consistency ratios for all customers were obtained as follows: 0.034,0.040,0.037,0.037,0.035,0.040,0.034,0.048,0.040,0.041 for the main CRs, and 0.008,0.008,0.058,0.008,0.010,0.008,0.008,0.008,0.093,0.008 for the sub CRs. As seen, they were all below 0.10.

Step 8. Calculating the relative importance of CRs. Pairwise comparisons of all customers are aggregated into one matrix, $\bar{R}$, with fuzzy arithmetic mean of r_{ij} with Eq. (8).

$$\bar{r_{ij}} = \frac{1}{t} \otimes (r_{ij1} \oplus \ldots \oplus r_{ijt}) \quad i \text{ and } j = 1, \ldots, k \text{ and } t=1,\ldots,s \tag{8}$$

Then the EA is applied (Chang, 1996) to obtain only the synthetic extent values as the HoQ is fuzzy and there is no need to obtain crisp values of RI_i. Where $TV_i = (tv_i^l, tv_i^{md}, tv_i^h)$ denotes the total fuzzy importance value of the each i^{th} object (CR), it is computed by using Eq. (9). Then all TV_i are summed to calculate $TV = (TV^l, TV^{md}, TV^h)$ and its inverse, Eq. (11). Finally, RI_i, of each CR is calculated with Eq. (12), where $RI_i = (RI_i^l, RI_i^{md}, RI_i^h)$.

$$TV_i = \sum_{j=1}^{k} \sum_{i=1}^{k} \overline{r_{ij}} \tag{9}$$

$$\sum_{i=1}^{k} TV_i = TV \tag{10}$$

$$[TV]^{-1} = \left(\frac{1}{TV^h}, \frac{1}{TV^{md}}, \frac{1}{TV^l}\right) \tag{11}$$

$$RI_i = TV_i \otimes [TV]^{-1} \tag{12}$$

Application: A sample calculation step by step is as follows:

Where, t denotes the number of customers, and $\overline{r_{13}}$ *denotes the final fuzzy value of* CR_1–CR_3 *relationship,* $\overline{r_{13}} = \frac{1}{t} \otimes [r_{131} \oplus r_{132} \oplus \ldots \oplus r_{13\,10}] = \frac{1}{10} \otimes [(1.00,1.00,1.00) \oplus (1.00,1.00,1.00) \oplus \ldots \oplus (2.00,3.00,4.00)] = (1.60,2.20,2.80)$

Where TV_1 *denotes the total fuzzy importance value of* CR_1, $TV_1 = \overline{r_{11}} \oplus \ldots \oplus \overline{r_{17}} = (1.00,1.001.00) \oplus \ldots \oplus (4.40,5.40,6.40) = (26.80,32.40,36.30)$. *Likewise, all* TV_i *values for all* CRs *and* $sub\text{-}CRs$ *were calculated to determine a single TV and* sub_TV *value, which were calculated as* $TV = TV_1 \oplus \ldots \oplus TV_7 = (84.28,102.60,119.18)$, *and* $sub_{TV} = TV_{21} \oplus TV_{22} \oplus\ TV_{23} = (13.40,15.80,18.25)$. *Then, inverse of* TVs *were calculated as* $[TV]^{-1} = (0.008,0.010,0.012)$, *and* $sub_{[TV]^{-1}} = (0.055,0.063,0.075)$.

At the end of step 8, RI_i *is of each of the main* CRs *were obtained and placed in the HoQ, such as relative importance of* CR_1 *is* $RI_1 = TV_1 \otimes [TV]^{-1} = (26.80,32.40,36.30) \otimes (0.008,0.010,0.012) = (0.225,0.316,0.431)$. $RI_{21}, RI_{22}, RI_{23}$ *values of* $sub\text{-}CRs$ *were normalized in order for the sum of* $RI_{21}^{md}, RI_{22}^{md}, RI_{23}^{md}$ *to be equal to* RI_2^{md} *before they were placed in the HoQ.*

Step 9. Determining the correlations among ECs. In this step, a square matrix is used as it supports asymmetric interrelationships between ECs. Each expert has one EC-EC linguistic relationship matrix for each CR as some ECs may have none effect on all CR's. Then, linguistic matrices are converted into fuzzy matrices to be used in Step 12.

Application: *The scale in (Maritan, 2015) was adopted in this step. The original version of this scale has three levels quantified with crisp values that are, 0 for no correlation, 1 for weak, 3 for medium, and 9 for strong correlations. We used its fuzzy version, where medium values of the fuzzy numbers corresponds to the crisp values of the scale levels, as follows: Negative High-NH (-4; -9; -9), Negative Medium-NM (-1; -3; -5), Negative Low-NL (0; -1; -2), no correlation (0; 0; 1,), and Positive Low-PL (0; 1; 2), Positive Medium-PM (1; 3; 5) and Positive High-PH (4; 9; 9). Since there were nine CRs and three experts, there were 27 matrices in total. Matrices of the first expert was given as an example in Fig. 3.*

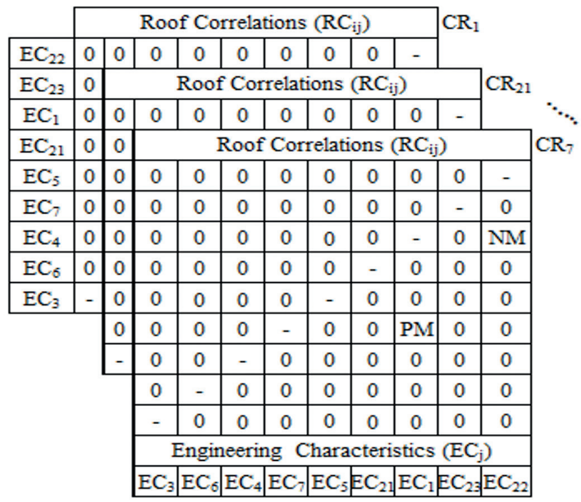

Fig. 3: Asymmetric Linguistic Correlation Matrices Regarding Each CR of Expert 1

Step 10. Determining the relative weights. The expert team identify the competitors and ask customers to make a competitive evaluation by using (1-5) numerical scale. Afterward, all matrices are aggregated into one with Eq. (13-14) where SC_i denotes the performance of the subject company and CC_i denotes the performance of the competitor under the i^{th} CR. Then the experts set goals regarding each CR and evaluate the relationship between the goals and CRs by using the same scale. In the end, individual evaluations of each expert are aggregated into one with Eq. (15) where SG_i denotes the strategic goal regarding the i^{th} CR.

$$SC_i = \frac{1}{t} \otimes (sc_{i1} \oplus sc_{i2} \oplus \ldots\ldots\ldots. \oplus sc_{it}) \tag{13}$$

$$CC_i = \frac{1}{t} \otimes (cc_{i1} \oplus cc_{i2} \oplus \ldots. \oplus cc_{it}) \quad i = 1, \ldots, k \text{ and } t = 1, \ldots, s \tag{14}$$

$$SG_i = \frac{1}{n} \otimes (sg_{i1} \oplus sg_{i2} \oplus \ldots \oplus sg_{in}) \quad i = 1, \ldots, k \text{ and } n = 1, \ldots, e \tag{15}$$

After that, the improvement ratio (IR_i), which is a score representing that if the subject company needs improvements in satisfying CRs to achieve strategic goals, is calculated with Eq. (16) (1.00 means that no

	SCi	CCi (European)	CCi (Asian)	SGi	IRi	SPi
CR_1	4	5	3			
CR_{21}	4	4	4			
CR_{22}	3	4	3			
CR_{23}	4	5	3			
CR_3	3	5	4			
CR_4	3	4	4			
CR_5	4	5	3			
CR_6	3	4	3			
CR_7	4	5	3			

(a)

	SCi	CCi (European)	CCi (Asian)	SGi	IRi	SPi
CR_1				4		1.50
CR_{21}				5		1.25
CR_{22}				4		1.20
CR_{23}				4		1.20
CR_3				4		1.50
CR_4				4		1.25
CR_5				4		1.25
CR_6				5		1.25
CR_7				4		1.50

(b)

	SCi	CCi (European)	CCi (Asian)	SGi	IRi	SPi
CR_1	3.70	4.50	3.10	4.33	1.17	1.42
CR_{21}	4.30	4.60	3.80	4.77	1.09	1.08
CR_{22}	3.50	4.10	3.50	4.07	1.14	1.13
CR_{23}	4.20	5	3.70	4.73	1.11	1.40
CR_3	3.40	4.40	3.50	4	1.18	1.42
CR_4	3.20	3.80	3.30	3.47	1.04	1.17
CR_5	3.90	4.60	3.20	4.33	1.11	1.42
CR_6	3.40	4	3.20	4.67	1.37	1.17
CR_7	4.20	4.40	2.90	4.47	1.03	1.50

(c)

Fig. 4: (a) Evaluations of customer 1 and **(b)** expert 1 **(c)** aggregated evaluations

improvement is necessary). Next, the experts determine sales points (SP_i) for each CR. Then SP_i ratings are aggregated into one with Eq. (17). According to Chan and Wu (2002), a sales point contains such information that characterizes the product selling ability of the subject company based on how well the subject product/design meets each customer requirement. A "strong" sales point means that the CR is critical and provides a competitive advantage. A "moderate" sales point implies that the importance of the CR and the competitive opportunity it provides is not so great. A "no" sales point means that the CR provides no opportunity and has no importance. Their numeric values are 1.5, 1.25, and 1, respectively. Then a triangular fuzzy absolute weight (AW_i) for each CR is calculated with Eq. (18). Finally, AW_i of CRs are defuzzified and normalized by dividing each normalized AW_i by the sum of all normalized AW_is to obtain crisp RW_is. In other words, weights of CRs in regards to competitive analysis are expressed as a percentage of the total with Eq. (19).

$$IR_i = \frac{SG_i}{SC_i} \quad i = 1, \ldots, \tag{16}$$

$$SP_i = \frac{1}{n} \otimes (\mathrm{sp}_{i1} \oplus \mathrm{sp}_{i2} \oplus \ldots \oplus \mathrm{sp}_{in}) \quad i = 1, \ldots, k \text{ and } n = 1, \ldots, e \tag{17}$$

$$AW_i = RI_i \otimes IR_i \otimes SP_i \tag{18}$$

$$RW_i = \frac{AW_i}{\sum_{i=1}^{k} AW_i} \quad i = 1, \ldots, k \tag{19}$$

Application: *In this step, customers' and experts' evaluations were obtained. Customer 1's and Expert 1's evaluation matrices can be seen in Fig. 4(a) and 4(b) respectively. Also, the aggregated evaluation matrix with IR_i was as in Fig 4(c).*

Some, numerical illustrations are as follows: Where SC evaluations were done by the customers and SC_1 denotes the performance of the subject company under the 1st CR, $SC_1 = \frac{1}{10} \otimes (sc_{11} \oplus \ldots \oplus sc_{1\,10}) = \frac{1}{10} \otimes (4 \oplus \ldots \oplus 4) = 3.70.$

Where CC evaluations were also done by the customers, and CC_1 denotes the performance of the competitor under the 1st CR, $CC_1 = \frac{1}{10} \otimes (cc_{11} \oplus \ldots \oplus cc_{1\,10}) = \frac{1}{10} \otimes (5 \oplus \ldots \oplus 5) = 4.50.$

Where SG evaluations were done by the experts, SG_1 denotes the strategic goal regarding the 1st CR, $SG_1 = \frac{1}{3} \otimes (sg_{11} \oplus sg_{12} \oplus sg_{13}) = \frac{1}{3} \otimes (4 \oplus 5 \oplus 4) = 4.33.$

Where IR_1 denotes the improvement ratio of the 1st CR, $IR_1 = SG_1/SC_1 = 4.33/3.70 = 1.17.$

Where SP evaluations were done by the experts, SP_1 denotes the sales point of the 1st CR, $SP_1 = \frac{1}{3} \otimes (sp_{11} \oplus sp_{12} \oplus sp_{13}) = \frac{1}{3} \otimes (1.50 \oplus 1.25 \oplus 1.50) = 1.42.$

With the completion of this step, AW_i and RW_i of each CR were calculated and placed in the HoQ in Fig. 8. A sample calculation is given below.

Where AW_1 denotes fuzzy absolute weight of the 1st CR, fuzzy $AW_1 = RI_1 \otimes IR_1 \otimes SP_1 = (0.22, 0.31, 0.43) \otimes 1.17 \otimes 1.42 = (0.37, 0.52, 0.71),$ *and normalized* $AW_1 = \frac{[0.37 + (0.52 * 4) + 0.71]}{6} = 0.53.$

Where RW_1 denotes the crisp relative weight of the 1st CR, $RW_1 = \frac{AW_1}{AW_1 + \cdots + AW_7} = \frac{0.53}{0.53 + \cdots + 0.12} = 0.33.$

Step 11. Determining the relative column weights and rankings. In this step, fuzzy relative column weights (RCW_j) of each EC is computed without interrelationships among ECs. Eq. (20) is used for the computations. All weights are normalized with Eq. (21). With the normalization, each weight is represented as a percentage of the total where i and $j=1,\ldots,m$ and CW_j and RCW_j are triangular fuzzy numbers. In the end, RCW_js are defuzzified with Eq. (5) and ECs are ranked according to their crisp weights.

$$CW_j = \sum_{i=1}^{k} C_{ij} \otimes RW_i \quad (20)$$

$$RCW_j = \frac{CW_j}{\sum_{j=1}^{m} CW_j} \quad (21)$$

Application: *RCW_j and rankings were calculated and placed in the HoQ, as in Fig. 8. Some sample calculations are provided below.*

Where CW_l denotes fuzzy column weight of EC_l $CW_1 = (C_{11} \otimes RW_1) \oplus ... \oplus (C_{17} \otimes RW_7) =$ [(0.66,0.76,0.86) $\otimes$ 0.33] $\oplus ... \oplus$ [(0.53,0.63,0.73) $\otimes$ 0.08] = (0.32,0.37,0.43). *Then, it was defuzzified to calculate the relative column weight.*

$$RCW_1 = \frac{CW_1}{CW_1 + \cdots + CW_7} = \frac{0.3724}{0.37 + \cdots + 0.13} = 0.18$$

Step 12. FCM analysis. Fuzzy correlation matrices belonging to each expert obtained in Step 9 are integrated into one individual matrix with Eq. (22) where the influence that the i^{th} EC on the i^{th} EC regarding the k^{th} CR of the same expert n is denoted as rc_{ijk}^{n}. The individual matrices obtained with the integration represents FCM adjacency matrices (maps) of the experts. Therefore, rc_{ij}^{n} values become arc values that are denoted as w_{ij}^{n}.

$$rc_{ij}^{n} = \sum_{k=1}^{K} rc_{ijk}^{n} RW_i = w_{ij}^{n} \quad (22)$$

After obtaining individual maps, they are re-integrated into one map to be used as an asymmetric roof matrix in the HoQ. There are arithmetic mean $W_{ij} = \sum_{n=1}^{N} \frac{w_{ij}^{n}}{n}$, or summation $W_{ij} = \sum_{n=1}^{N} w_{ij}^{n}$ operators for the map integration. After constructing the integrated map, static or dynamic analysis can be done. We applied static analysis as the system we modelled is irrespective of the behaviour of the system over time. Both for the map integration and dynamic analysis, FCM Expert software (Felix et al., 2017) and for extensive maps and generating different scenarios Mental Modeller software (Gray et al., 2013) can be used.

In the scope of static analysis, the density of the map, centrality, and strength of the nodes are examined (Stach, Kurgan, & Pedrycz, 2010). Density D is an indication of the complexity of the map. It is the ratio of the number of the edges, E, to the maximum number of the edges that the map can have. It is formulated as $D = \frac{E}{V(V-1)}$, where V is the number of concepts (nodes). The degree of a node deg_i is the sum of incoming and outgoing edges of the node. The number of incoming edges of a node j is called in-degree deg_j^{in}, and the number of outgoing edges of a node is called out-degree deg_j^{out}. The degree of a node represents its centrality. Higher the value of the centrality, the higher the number of interactions it has and so significant the node to be. The total strength value of a node j is val_j. It is the sum of the absolute weights of all incoming edges to the subject node $\left(val_j^{in} = \sum_{i \neq j} |w_{ij}|\right)$ and all outgoing edges from the subject node $\left(val_j^{out} = \sum_{i \neq j} |w_{ji}|\right)$. The strength of a node denotes its significance/importance. For further information regarding FCM analysis, please refer to Axelrod (1976), Christoforou & Andreou (2017), Felix et al. (2017), Kosko (1986), Papageorgiou (2012), Papageorgiou & Salmeron (2013) and Tsadiras (2008).

Application: *A set of nine matrices that belongs to each expert obtained in Step 9 were integrated into one individual matrix with Eq. 22. For example, the integrated effect of EC_7 on EC_1 regarding all CRs based on the evaluations of Expert 1 was calculated as below. The integrated matrix of Expert 1 and the final matrix be seen in Fig. (5-6) respectively.*

$$rc_{71}^{1} = rc_{711}^{1} RW_1 \oplus rc_{71-21}^{1} RW_{21} \oplus rc_{71-22}^{1} RW_{22} \oplus rc_{71-23}^{1} RW_{23}$$
$$\oplus\, rc_{713}^{1} RW_3 \oplus rc_{714}^{1} RW_4 \oplus rc_{715}^{1} RW_5 \oplus rc_{716}^{1} RW_6 \oplus rc_{717}^{1} RW_7 =$$
$$[(1.00,3.00,5.00) \otimes 0.33] \oplus ... \oplus [(1.00,3.00,5.00) \otimes 0.08]$$
$$= (0.05,0.13,0.22) = w_{71}^{1}$$

Then, the final map, Fig. 7, was calculated with the arithmetic mean operator as the summation operator requires the use of a threshold function (e.g., Sigmoid

EC22	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	-	-	-
EC23	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	-	-	-	0	0	0
EC1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	-	-	-	0	0	0	-0.45	-0.42	-0.18
EC21	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	-	-	-	0	0	0	0.06	0.13	0.13	0	0	0
EC5	0	0	0	0	0	0	0	0	0	0	0	0	-	-	-	0	0	0	0	0	0	0.07	0.20	0.34	-0.34	-0.20	-0.07
EC7	0	0.03	0.06	0	0	0	0	0	0	-	-	-	0	0	0	0	0	0	0.05	0.13	0.22	0.20	0.45	0.45	0	0	0
EC4	0	0	0	0.02	0.05	0.05	-	-	-	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
EC6	0	0	0	-	-	-	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
EC3	-	-	-	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0.08	0.15	0	0	0
	EC3			EC6			EC4			EC7			EC5			EC21			EC1			EC23			EC22		

Fig. 5: Individual Roof Matrix of Expert 1

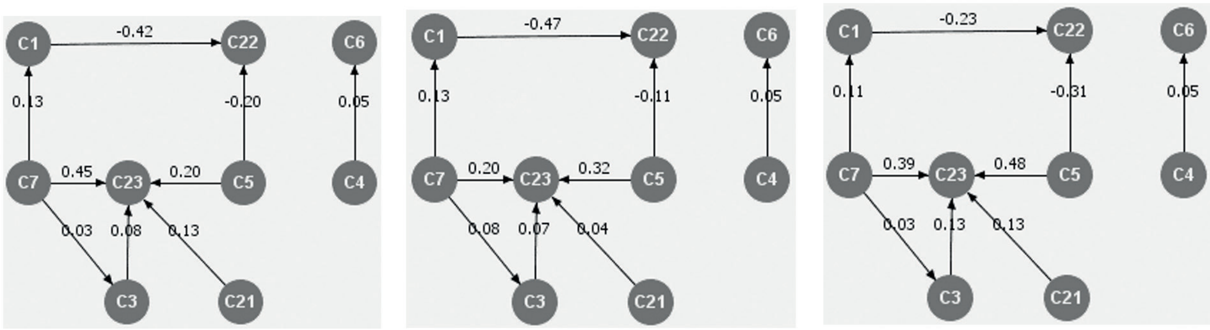

Fig. 6: FCM Representations of Roof Matrices Belongs to the Experts correspondingly (The capital Cs in the nodes denote the "concepts" in FCM analysis. Their corresponding variables are ECs in QFD method.)

function) to transform summated fuzzy values in the interval of [-1, 1]. After that adjacency matrix was placed as a roof matrix in the HoQ in Fig. 8. Finally, the static analysis was done and summarized in Table 3.

Where W_{71} denotes the influence of the 7th EC on the 1st EC, which is the directed arc weight between ***EC_7-EC_1,***

$$W_{71} = \frac{w_{71}^{1} \oplus w_{71}^{2} \oplus w_{71}^{3}}{3} = \frac{(0.05,0.13,0.22) \oplus (0.05,0.13,0.22) \oplus (0.03,0.11,0.15)}{3} = (0.04,0.13,0.20).$$

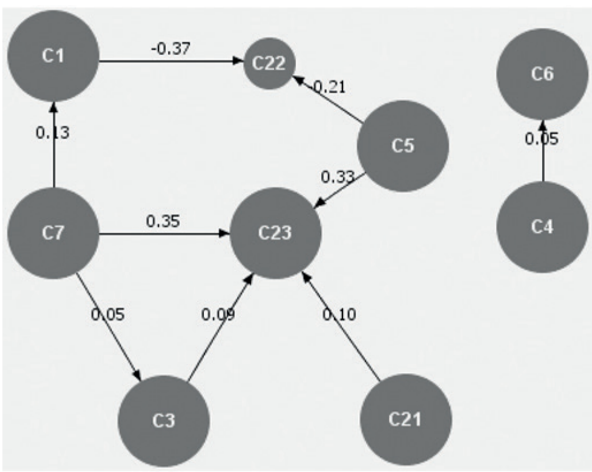

Fig. 7: The Final FCM

Step 13. Determining the final column weights and rankings. The ranking calculated in step 11 is based on only CR satisfying capabilities of ECs. Hence, the better an EC is capable of satisfying CRs, the more critical it is. Asymmetric EC-EC interrelationships are considered additionally here in Step 13. The desired scenario in this step is determining an EC of which CR satisfaction capability is high but total casual effect on other ECs (val_j^{out}) is low. The geometric mean method is used to aggregate those values. However, multiplying CW_j by (val_j^{out}) will lessen the CR-EC relationship effect on the final importance. Because of that, the inverse of (val_j^{out}) is taken into consideration not to lessen the effect. Of the ECs (concepts in FCM) which have none outgoing edges, (val_j^{out}) values are set to 0.01. Therefore, the values of $(val_j^{out})^{-1}$ become in the interval of [0,100]. This requires the change of the range of CW_j from [0, 1] to [0, 100] as well. To do that, CW_j is multiplied with a coefficient, 100. Then the final importance weight of an EC is calculated with Eq. (23). Finally, they are defuzzified with Eq. (5) and re-ranked according to their crisp weights.

$$FW_j = \sqrt[2]{100 * CW_j * (val_j^{out})^{-1}} \tag{23}$$

The general interpretation of FW_j values can be as follows: Higher FW_j means that the j^{th} EC has a higher effect on CRs and lower effects on other ECs. Hence, it becomes an easily manageable and applicable EC. Also, the tasks related to that EC can be implemented firstly due to any change in that EC will have less effect on the other ECs. It may have a high level of strategic importance, and provide competitive advantages and market opportunities to the company. Additionally, since the value of the final weight depends on the column weight, and the value of the column weight indirectly depends on the improvement ratio, a higher final weight may point out more significant differences between SC_i and SG_i. On the other hand, lower values mean that the EC has a weaker effect on CRs and higher effects on other ECs. Therefore, it is not an easily manageable and applicable EC. Implementation priority may not be given to its related tasks because any change in that EC will have a significant effect on the other ECs. Probably, its strategic importance is low, so it provides lower competitive advantages and market opportunities to the company. Additionally, a lower final weight may point out smaller differences between SC_i and SG_i. In other words, there is not much to do for improving the product/design with respect to that EC.

Application: *With the end of this step, final weights of ECs and their final rankings based on crisp values were obtained and placed in the HoQ as in Fig. 8. Calculation of the final weight of EC1 is given as an example as follows: Where* $val_1^{out} = \sum_{i\neq 1}|w_{1i}| = |-0.37| = 0.37$ *as obtained from Figure 5,* $FW_1 = \sqrt[2]{100 * CW_1 * (val_1^{out})^{-1}} = \sqrt[2]{100 * 0.37 * \frac{1}{0.3724}} = 10.03.$

6. FINAL RESULTS and DISCUSSION

In this study, an integrated QFD methodology was proposed to rank CRs with considering asymmetric interrelationships among ECs quantitatively. It was applied to a company that globally operates and produces sheet metal dies for Tier 1 and Tier 2 suppliers in the automotive industry. The subject product is a sophisticated tool that inherits complex CR-EC relationships and EC interrelationships.

The application of IA for investigating the relationships between CRs and ECs enabled us determining some high-grade relationships, which could cause time and money loss to the company. AD approach of Çebi and Kahraman (2011) was adopted in this study. The aim was obtaining a product design of which couplings in a tolerable limit defined by the experts. As explained in step 6, the final CR-EC relationship matrix was a decoupled matrix $\widetilde{C} = 0.06, 0.07, 0.09)$ in the limits of the tolerance, $\gamma = (0.1, 0.1, 0.1)$.

According to Table 3, the density of the map is very low. It means that there are not many edges or casual effects between ECs so the complexity of the map is low. However, since the subject problem is an engineering problem regarding a highly sophisticated product, the magnitude of the effects may be important. The center and also the most influential-strongest node of the map is EC_{23}. The node that has the most casual effect on other nodes is EC_5 based on its val_5^{out}. There are four driver nodes and three receiver nodes on the map. As the map is acyclic as seen in Fig. 7, any change in one concept does not have an indirect effect on itself. If the map was cyclic, CRs and ECs should have been revised, or granulated further. Please refer to Osoba and Kosko (2017) for more information about cyclic maps.

Moreover, it is observable that considering EC-EC interrelationships changes the order, Fig. 7 and Table 4. The rankings of the three strongest ECs (EC_1, EC_5, EC_7) regarding their val_j^{out} dramatically moved to lowest levels. High column weight and casual effect values of EC_1 and EC_5 caused them to move lower levels in the ranking. The highest sales point and very high casual effect values of EC_7 made it to be in the last rank. EC_4 is also in the last four rankings just because of its lowest column weight value. Any change in the values of that four ECs will profoundly affect the other ECs. If other ECs are adversely affected, their corresponding CRs may not be satisfied. Hence the decision-makers have to be careful with them. Thus, they are the least manageable and most critical ECs.

Regarding EC_4, the engineers should consider if it is worth to make any change in it. Even though it is a manageable EC regarding its effect on other ECs, its CR satisfying capability is very low. Therefore, it is better to investigate the final map. If its centrality is high even though its casual effect is at a minimal level, it may not be preferential to make any change because it will both directly and indirectly, affect other ECs. If not, an implementation priority can be given to it. In our example, implementation priority can be given to EC_4 because it only affects EC_6 and EC_6 has none effect on any other ECs.

Regarding the ECs in the first three ranking, namely, EC_{21}, EC_{23} and EC_3, their column weights are very high contrary to their casual effects on other ECs. It can be defined as a most desirable situation. Any task implementations regarding them will not affect other ECs but will satisfy most of the CRs. Hence, they are the most manageable ECs, and their corresponding CRs are better satisfiable CRs. Finally, there are two ECs left to discuss about, EC_{22} and EC_6. They are in the middle of the ranking with moderate values of val_j^{out} and CW_j. They moved from the lower levels to middle levels in the ranking.

For a general overview, first the proposed model has demonstrated that AD is a very suitable method to be used with QFD as they have a common ground

Table 3: Outputs of the Static Analysis of the Final Map

Density	Concept			Centrality			Strength	Type
	C_1	1	1	2	0.13	0.37	0.50	Ordinary
	C_{21}	0	1	1	0	0.10	0.10	Driver
	C_{22}	2	0	2	0.58	0	0.58	Receiver
	C_{23}	4	0	4	0.87	0	0.87	Receiver
0.125	C_3	1	1	2	0.05	0.09	0.14	Ordinary
	C_4	0	1	1	0	0.05	0.05	Driver
	C_5	0	2	2	0	0.54	0.54	Driver
	C_6	1	0	1	0.05	0	0.05	Receiver
	C_7	0	3	3	0	0.40	0.40	Driver

Table 4: Summary of the HoQ

Name	Ranking	Final Ranking	RI_i	IR_i	SP_i	RW_i	CW_j	val^{out}_j
EC_{23}	5	↑ 1	0.08	1.11	1.42	0.08	0.26	0
EC_3	3	↑ 2	0.24	1.18	1.42	0.25	0.37	0.09
EC_{21}	2	↓ 3	0.01	1.09	1.08	0.01	0.37	0.10
EC_6	7	↑ 4	0.03	1.37	1.17	0.03	0.03	0
EC_{22}	8	↑ 5	0.04	1.14	1.17	0.04	0.03	0
EC_1	4	↓ 6	0.32	1.17	1.42	0.32	0.37	0.37
EC_5	1	↓ 7	0.17	1.11	1.42	0.17	0.43	0.54
EC_4	9	↑ 8	0.03	1.04	1.17	0.02	0.03	0.05
EC_7	6	↓ 9	0.08	1.03	1.5	0.08	0.13	0.40

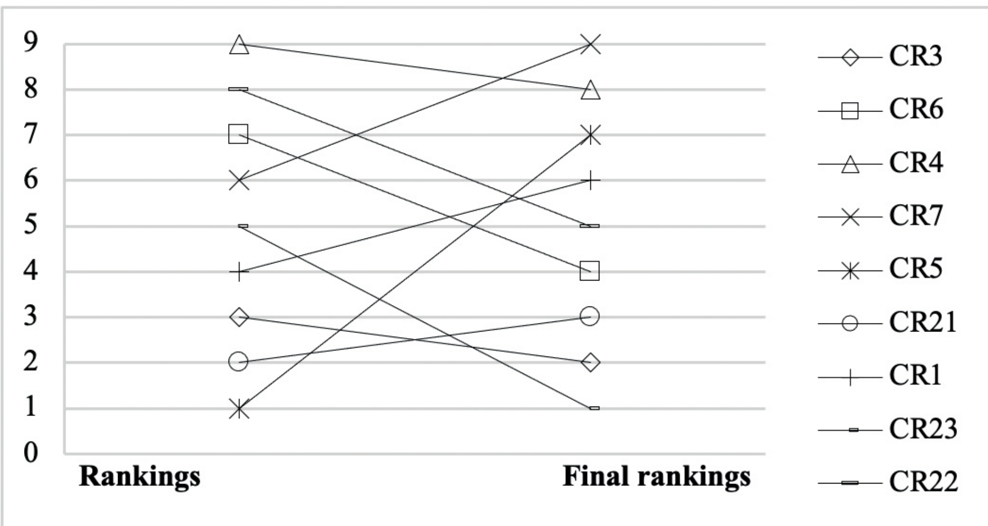

Fig. 7: Comparisons of the Rankings

regarding design domains. It is an efficient method to manage the design process by the decomposition, and to reduce the complexity of the design by managing the couplings in CR-EC relationship matrix. Second, fuzzy AHP is also a must used method in QFD applications, where more than one expert is involved in, to obtain consistent evaluations. The last but not the least, use of asymmetric roof matrix is crucial as it better captures the EC-EC relationships similar to what Fazeli & Peng (2021) highlighted and proved in their study. With the same purpose of ours the authors used *DEMATEL* but under the assumption of CRs

were not correlated. They also assumed that *EC-EC* relationships stay same under different *CRs*. However, value of a particular *EC-EC* relationship may change depending on the *CR* considered. In this respect, investigating *EC-EC* relationship for each *CR* is better appropriate to real-life problems.

What is more, *FCM* is an appropriate and practical method to be used for analysing the asymmetric roof matrix by quantifying correlations. It provides additional information for managerial practices/ implications, such as determination of the strongest *EC*, the *EC* that has the most casual effect on other *ECs*, and the presence of cyclic or acyclic relationships among ECs. To the best of our knowledge, *FCM* method has not been used with *QFD* in the literature.

The present study was subject to some potential practical and methodological weaknesses, such as number of experts, and concepts (*ECs*) are small, and the fuzzy scale used is not sensitive enough. A much granulised fuzzy scale could has been utilized if the experts were willing to use in their judgements.

For further research, dynamic analysis of *FCMs* can be considered. It could not be applied in this study as the number of the concepts and experts was small, the density of the map was low, and the fuzzy scale was not sensitive enough. Additionally, hesitant fuzzy sets can be employed. When hesitancy is considered as the uncertainty degree of the fuzzy information decision-makers provided, measuring uncertainty of hesitant information with the help of statistical approaches in machine learning would be interesting. For example, in case of having an extensive group of decision makers (that yields to large enough sample/data), some robust hesitancy functions with sub-sampling techniques could be created for defining low and high level (or null and full) hesitant sets.

Roof Correlations (RC_{ij})								
0 0 0	0 0 0	0 0 0	0 0 0	0 0 0	0 0 0	0 0 0	0 0 0	- - -
0 0 0	0 0 0	0 0 0	0 0 0	0 0 0	0 0 0	0 0 0	- - -	0 0 0
0 0 0	0 0 0	0 0 0	0 0 0	0 0 0	0 0 0	- - -	0 0 0	-0.42 -0.37 -0.16
0 0 0	0 0 0	0 0 0	0 0 0	0 0 0	- - -	0 0 0	0.04 0.10 0.11	0 0 0
0 0 0	0 0 0	0 0 0	0 0 0	- - -	0 0 0	0 0 0	0.13 0.33 0.43	-0.32 -0.21 -0.07
0.00 0.05 0.08	0 0 0	0 0 0	- - -	0 0 0	0 0 0	0.04 0.13 0.20	0.15 0.35 0.38	0 0 0
0 0 0	0.02 0.05 0.05	- - -	0 0 0	0 0 0	0 0 0	0 0 0	0 0 0	0 0 0
0 0 0	- - -	0 0 0	0 0 0	0 0 0	0 0 0	0 0 0	0 0 0	0 0 0
- - -	0 0 0	0 0 0	0 0 0	0 0 0	0 0 0	0 0 0	0.01 0.09 0.17	0 0 0

		Engineering Characteristics (EC_j)												
	RI_i	EC_3	EC_6	EC_4	EC_7	EC_5	EC_{21}	EC_1	EC_{23}	EC_{22}	IR_i	SP_i	AW_i	RW_i
Customer Requirements (CR) CR_3	0.17 0.24 0.33	0.73 0.83 0.93	0 0 0	0 0 0	0 0 0	0 0 0	0 0 0	0 0 0	0 0 0	0 0 0	1.18	1.42	0.28 0.40 0.55	0.25
CR_6	0.12 0.03 0.04	0 0 0	0.66 0.76 0.86	0.26 0.36 0.46	0 0 0	0 0 0	0 0 0	0 0 0	0 0 0	0 0 0	1.37	1.17	0.04 0.05 0.06	0.03
CR_4	0.02 0.03 0.04	0 0 0	0.33 0.43 0.53	0.66 0.76 0.86	0 0 0	0 0 0	0 0 0	0 0 0	0 0 0	0 0 0	1.04	1.17	0.03 0.04 0.05	0.02
CR_7	0.05 0.08 0.12	0 0 0	0 0 0	0 0 0	0.66 0.76 0.86	0 0 0	0 0 0	0.53 0.63 0.73	0 0 0	0 0 0	1.03	1.50	0.08 0.12 0.20	0.08
CR_5	0.12 0.17 0.24	0.46 0.56 0.66	0 0 0	0 0 0	0 0 0	0.8 0.9 1	0.06 0.16 0.26	0 0 0	0 0 0	0 0 0	1.11	1.42	0.19 0.27 0.39	0.17
CR_{21}	0.01 0.01 0.03	0 0 0	0 0 0	0 0 0	0 0 0	0.53 0.63 0.73	0.73 0.83 0.93	0.4 0.5 0.6	0.4 0.5 0.6	0 0 0	1.09	1.08	0.01 0.02 0.03	0.01
CR_1	0.22 0.31 0.43	0 0 0	0 0 0	0 0 0	0.13 0.23 0.33	0.6 0.7 0.8	0.66 0.76 0.86	0.66 0.76 0.86	0.4 0.5 0.6	0 0 0	1.17	1.42	0.37 0.52 0.71	0.33
CR_{23}	0.03 0.08 0.16	0.4 0.5 0.6	0 0 0	0 0 0	0 0 0	0.26 0.36 0.46	0.6 0.7 0.8	0.46 0.56 0.66	0.73 0.83 0.93	0 0 0	1.11	1.40	0.06 0.13 0.26	0.08
CR_{22}	0.02 0.04 0.09	0.73 0.83 0.93	0 0 0	0 0 0	0 0 0	0.26 0.36 0.46	0.66 0.76 0.86	0.46 0.56 0.66	0.4 0.5 0.6	0.66 0.76 0.86	1.14	1.13	0.03 0.06 0.12	0.04
	CW_j	0.32 0.37 0.43	0.03 0.03 0.04	0.02 0.02 0.03	0.09 0.13 0.17	0.37 0.42 0.49	0.31 0.37 0.44	0.32 0.37 0.43	0.21 0.25 0.30	0.02 0.02 0.03				
	Defuzzified CW_j	0.37	0.03	0.03	0.13	0.43	0.37	0.37	0.26	0.03				
	RCW_j	0.18	0.02	0.01	0.07	0.21	0.18	0.18	0.13	0.01				
	Rankings	3	7	9	6	1	2	4	5	8				
	100*CW_j	37.37	3.27	2.82	13.49	42.85	37.38	37.24	25.67	29.98				
	val_j^{out}	0.09	0.01	0.05	0.40	0.54	0.10	0.37	0.01	0.01				
	$1/val_j^{out}$	11.11	100	20	2.50	1.85	10	2.70	100	100				
	FW_j	20.38	18.08	7.51	5.81	8.91	19.33	10.03	50.67	17.32				
	Final Rankings	2	4	8	9	7	3	6	1	5				

Fig. 8: HoQ with the rankings and final rankings

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APPENDIX

CR1 (Repeatability). A car consists of approximately 1000 sheet metal parts that have to fit each other and other elements like molded plastics, injected castings and machined parts in a 0.2-2 mm tolerance. Hence, component fitness is crucially important for OEMs and so providing perfectly fitting sheet metal parts to OEMs for Tier 1 and Tier 2 suppliers. In this respect, repeatedly manufacturing dimensionally precise parts is a critical CR.

CR2 (Visual quality of stamped parts). Trimming burrs, material thinning and wrinkles are the factors affecting the visual quality of stamped parts. Trimming burrs can cause assembly problems, and employee injuries. Thinning and wrinkling affect the strength and durability of stamped parts which are very critical for some security parts like bumpers. Additionally, if the faulty part is a visible body part of a car, it may hurt consumers as well. In this study, they are denoted as CR21, CR22, and CR23 respectively.

CR3 (High production speed. OEMs develop or design mutual/identical automobile components for the purpose of mass production and cost reduction. Resultantly, these components have to be stamped over 2 million per year. Hence, high production speed is an important criteria for customers.

CR4 (Easy accessibility of standard components in sheet metal dies). Dies sometimes are transferred from one stamping facility to another one in a different country. In this case, they can be fixed easily, timely and cheaply only when their standard parts conform to global standards. Resultantly, standardization of die elements is crucial for customers.

CR5 (Long lifetime of tool steels used for trimming and cold forming in dies). Tool steels that are inside of the die wear out and have to be replaced several times during the lifetime of the die. However, they are the most expensive parts of dies as they are custom made. Once they wear out, it takes around five weeks to reproduce them. Such a long time may cause a halt of the production. Therefore, using tool steels with long lifetime is critical.

CR6 (Ease of replacement). Sheet metal presses have to be in production continuously except maintenance, and change times to meet the cost. However, during the production, some critical elements of dies, like piercing punches need replacements several times. If the replacement is easy, the duration of the halt of production decreases. Therefore, the ease of replacement becomes vital for the customers.

CR7 (Conformity of design data with the sheet metal die). Dies are shipped to customers with design data, and customers use the data for maintenance, repair and replacement. If the design data differs from the die, it requires additional labor for fixing the die, and results in increased maintenance/repairing. Therefore, dies should be produced according to the data.

EC1 (The repeatability of CNC machines). Die elements are manufactured in a very tight tolerance for example 0.01-0.10 mm, in CNC machines. Hence their dimensional precision heavily depends on the precision and tolerance interval of the machines. If die elements are manufactured in high technology machines, dies can stamp sheet metals precisely and repeatedly in accordance with the data. Hence, CR1 can be satisfied with EC1 as the repeatability of the sheet metal part production can be realized with the repeatability of the CNC machines used for the die production.

EC21 (Cutting clearance). Trimming burrs are one of the plastic deformation types in forming sheet metals. They can be eliminated by adjusting the cutting clearance, which is the gap between the punch and the die, to an optimum level.

EC22 (Surface roughness of the tool steels). Material thinning is also a type of plastic deformation. It can be eliminated with using proper tool steel regarding its roughness.

EC23 (Blank holder pressure/force). The blank holder holds the sheet metal in between upper and lower parts of the die while the punch forces the sheet metal into the die. Instead of applying a constant pressure to form the sheet metal, applying a variable pressure depending on the type of sheet metal may prevent wrinkling.

EC3 (Strokes per minute-SPM). Production speed can be increased with the increase of spm. Hence CR3 can be satisfied with the EC3.

EC4 (Ratio of standardized elements). The ratio of globally standard components to the total number of components in a die indicates that fixing the die can be done quickly and cheaply. Hence, CR4 can be satisfied with EC4.

EC5 (Hardness of tool steels). Long lifetime or durability of trim and form steels used in a sheet metal die depends on the hardness of materials used. Chemical properties like carbon ratio, physical properties like shear resistance, length, and temperature of hardening and tempering processes affect the tool steels. The most delineative indicator of these properties is the Rockwell Hardness (HRC).

EC6 (Replacement time). Guiding elements, active surface parts, trim and piercing matrices, trimming and piercing punches are some parts which are replaced frequently. Sometimes, replacements should be done during the production; in other words, when die is mounted on the press. Therefore, these elements should be designed with considering easy replacement criteria of customers. However, there may be some design limits. Time needed to change this kind of elements in minutes can be an indicator of CR6. If the time consumed during a replacement is high, it means that replacing that specific element is not easy.

EC7 (Number of software). Special software in CAD, CAM, CAE, process management and reverse engineering eliminate human errors and guarantee that the manufactured sheet metal die conforms with its design. Therefore, the number of software can be a good indicator of CR.