On Application of Fuzzy Logic to Decisions Making in Solving Inventive Problems

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Abstract — **Several methods of inventive problem solving offer structured recommendations on how to proceed with a solution. However, a problem solving expert still needs to convert linguistic recommendations into quantitative or binary parameters. This conversion is usually made by applying hidden rules, or relying on intuition, and only on a rare occasion the expert goes through a sequence of explicit decision making steps. Even worse, this decision making process may take place subconsciously, without any formal scoring process. It is proposed to consistently handle all linguistic derivations that allow "IF-THEN" formulation by applying Fuzzy Logic (FL).**

Keywords: Inventive Problems, decision rules, Fuzzy Logic.

I. Introduction

When solving an inventive problem, it is often necessary to manipulate with linguistic (subjective) knowledge, which is difficult to express in quantitative terms [1]. This knowledge may include information about the object (product or process to be improved), goals and constraints, success criteria, problem solving rules and so forth. A problem solving expert often needs to quantify, one way or another, multiple verbal statements, or convert certain linguistic recommendations into a binary decision (Yes or No). Such a conversion or quantification is usually done implicitly, based on intuition and without formal analysis. In fact, while several approaches to solving inventive problems and to creativity in general claim to be "an exact science" [2], they do not meet very basic scientific criteria, such as reproducibility and independence of results on the subject (person) solving the problem. Different teams working on the same task will often generate different solutions. To big extent, this is due to verbal, non-quantitative character of the rules used in the solution process. Other reasons include vague recommendations and ambiguity in determining the boundaries of the system under consideration.

The approach described below offers a more logical and consistent way to do that.

While in the example that follows considered are problem solving rules, this approach can be applied in the same manner to formalizing project goals and other categories listed above. The outlined logic can also be coded in a software application.

II. Background

A. Selected problem solving rules

In this note, we consider application of problem solving tools recommended by the Theory of Inventive Problem Solving, or TRIZ [1]. One of these recommendations suggest ways to *trim* (eliminate) troublesome components of a technical system. The trimming concept means that a *component* of a *system* or a process is eliminated and its *useful functions transferred* to other components [3]. One of the trimming recommendations can be formulated as follows: "If *functional significance* of a component is low and its cost is medium and *its problem rank* is medium, then it is a likely candidate for trimming". To follow this recommendation, a practitioner needs to convert it, one way or another, into a binary decision (to trim or not). This is usually done by combining functional significance, cost and problem rank and ranking the components of a technical system on a scale from 0 to 1 (or, 0 to 100), with the first candidate to be trimmed having the highest rank (the largest number).

Another example is classification of a given component as belonging to a *supersystem* (a higher-level system, which includes the system under consideration as a sub-system [3]) or a *system*. A statement like "If a component passes through a system by transit, or it cannot be modified, or it is located very far from the system, then it likely belongs to the supersystem" needs to be correctly interpreted when a functional model is built [3].

B. Fuzzy Logic

A set of user-supplied human language rules, used in solving inventive problems, can be better handled by fuzzy logic (FL), specifically, by a fuzzy inference system (FIS) [4]. A FIS can consist of a number of conditional "IF-THEN" rules. The "IF-THEN" format of the rules makes it easier for a problem solving expert to verbalize his insights, which can be then coded in software. As many rules as needed can be supplied to describe the decision making process adequately.

Suppose that statement **A** says "a system cannot be modified". In standard conditional logic (CL), this statement is either true or false. In FL, the degree of truth is allowed to vary between 0 and 1, so it can be said that the system cannot be modified to the degree of 0.8. Further on, if in CL the inference rules take the form "**p** -> **q**", in FL it is possible to say "if **p** is half true, **q** is 60% true".

Expressed in the FL format, the recommendations have to become more specific, and the fuzzy sets allow greater flexibility in doing that. Suppose one of the rules states that *"If (a component cannot be modified) then (it likely belongs to a supersystem)"*. Both variables, *cannot be modified* and *likely belongs,* have to be mapped to ranges of values (Fig. 1). FIS's rely on membership functions, which are curves that define the truth mapping for each fuzzy statement. The degree to which any fuzzy statement is true is denoted by a value between 0 and 1. Fig. 1 states that if *"strength of constraints to modify"* a component equals to 7 on the 0 to 10 scale, its membership functions for *"can be somewhat modified"* and *"cannot be modified"* are .42 and .75, respectively. In other words, *"strength of constraints to modify"* =7 resides in the fuzzy sets *"can be somewhat modified"* and *"cannot be modified"*, to different degrees of similarity. –Combining the two rules shown in Fig. 1 (more details below), one can get a conclusion that the likelihood that the element belongs to the supersystem is μ=0.42, if strength of constraints to modify the element is 7. And, if the element was totally fixed (no freedom to modify at all), it would belong to the supersystem to the degree of 0.5 (see below) - this is now a specific meaning of *likely belongs*.

A typical configuration of a FIS is shown in Fig. 2 [4]. The fuzzifier converts crisp input values (like *"strength of constraints to modify"* =7) into fuzzy sets. The rules, which are activated in the inference engine, map fuzzy sets into fuzzy sets, and operate in terms of linguistic variables. The inference engine combines input rules, using rule composition, implication and aggregation. It maps fuzzy sets into fuzzy sets. The two basic type of inference engine are composition-based (first aggregate, then inference) and individual rule-based (first inference, then aggregate). The composition-based engine aggregates all rules in one fuzzy relation, which is then combined with the fuzzified inputs to obtain the fuzzy control output. The individual rule-based engine fires each rule individually and then computes the control output, using the union or intersection of the individual fuzzy sets. Different FL inferential procedures have been developed. The defuzziifer maps output sets into crisp numbers, which can be interpreted by a user.

Once the rules have been established, a FLS can be viewed as just a mapping from inputs to outputs.

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III. EXAMPLE: TRIMMING COMPONENTS OF AN OFFSHORE FLOATING WIND TOWER

Considered here is an example of a decision making procedure, namely, whether a design component of an offshore floating wind tower should be trimmed. This decision is made based on the three inputs: functional significance, cost and the problem rank, which is an integral measure of complications related to operation and maintenance of the component. Each input can take one of three linguistic values: low, medium, and high, and the recommendation to trim the component can take one out of five values: weak, weak to neutral, neutral, neutral to strong, strong. The subjective knowledge, expressed in terms of these values, is presented as a 3 x 3 x 3 cube, with the three inputs mapped along its edges and with a respective strength of the recommendation to trim in each cell. To simplify the example, it is assumed that cost and problem rank indices are combined in a "Cost & Problem Rank", which results in the matrix shown in Table 1. The table represents 9 rules; e.g., the first rule R_{11} is *"IF Functional Significance is low AND Cost & Problem Rank is low, THEN strength of recommendation to trim is neutral"*. The approach based on the AND rules is more general; e.g., any OR rule can be reduced to a number of ANDs.

The system under consideration in this example is an offshore floating wind tower (Fig. 3). Functionality and Cost & Problem Rank of its components were determined as a result of Function Analysis [1, 3], which involved 3 steps. At the first step, components of the technical system and supersystem were identified. At the second step, it was determined which components interact with each other. At the third step, functions performed by the components were identified and classified as useful or harmful functions, and the level of performance for useful functions was evaluated. Then Functionality of a component was determined based on based on the amount and level of performance of the useful functions, performed by the component. Cost & Problem Rank was based on the amount of harmful functions and the component cost. The results are shown in Fig. 4, where the components of the technical system are also listed. One of the components for which the decision making process is less obvious is the support (the tower itself). This component has high Functional Significance but also high Problem & Cost Rank (primarily due to high cost). We leave aside the question how to transfer useful functions of the support if it is trimmed (eliminated). This is a matter of the subsequent inventive solution process.

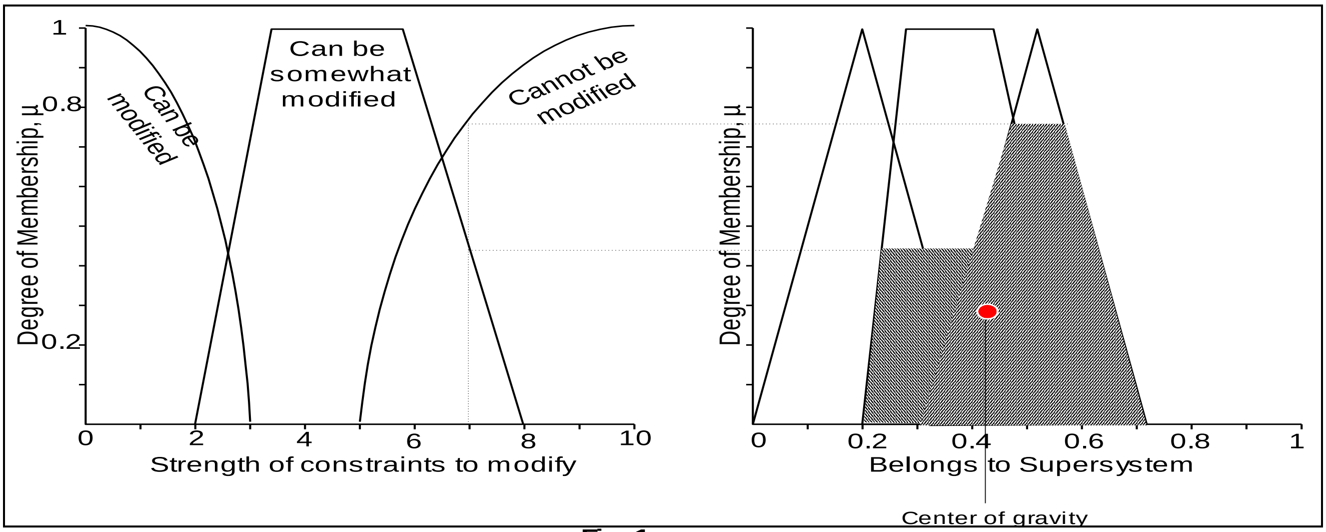

Fig. 1

Fig. 1. Membership functions for the variable "strength of constraints to modify".

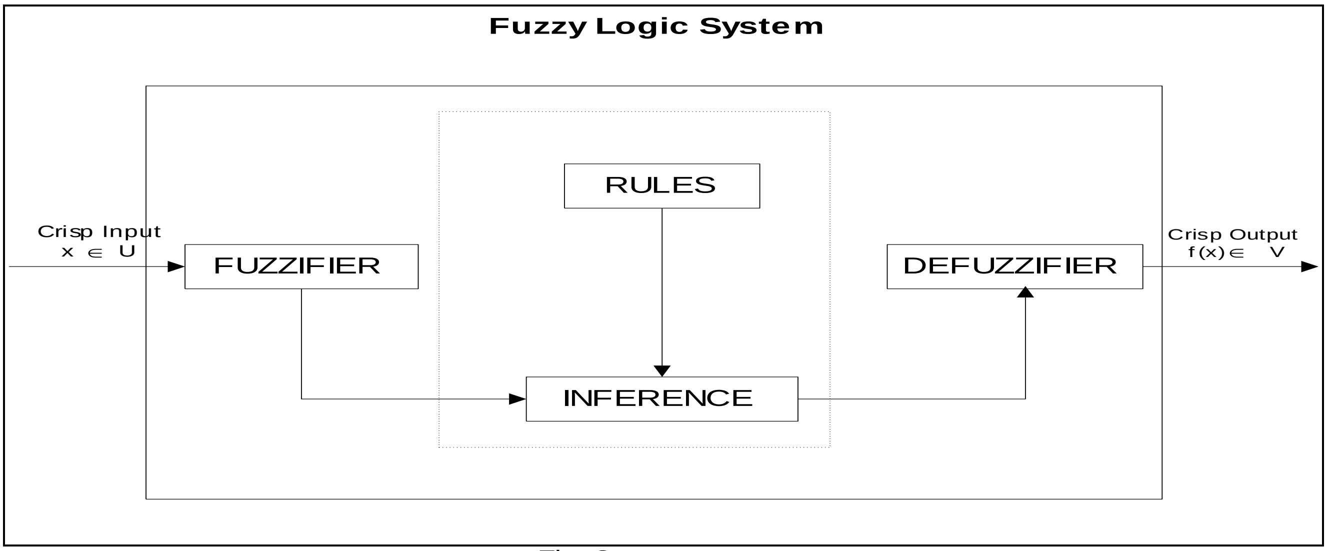

Fig. 2

Fig. 2. Configuration of a Fuzzy Logic System.

TABLE 1. RECOMMENDATION TO TRIM

Second input: Cost & Problem Rank --→

First input: Functional <---Significance

	Low	**Medium**	**High**
Low	Neutral	Neutral To Strong	Strong
Medium	Weak to Neutral	Neutral	Neutral To Strong
High	Weak	Weak to Neutral	Neutral To Strong

The decision making procedure, implemented in a FIS, is illustrated by plots in Fig. 5. The input values for the support (tower) are: Functionality = 14, Cost & Problem Rank = 21, or, after scaling each variable to the 0-10 scale, Functional Significance = 7, Cost & Problem Rank = 7. Each of these inputs belongs to two fuzzy sets for the respective variables: medium and high. The four rules which fire are enclosed in the bold square in Table 1.

The FL procedure, illustrated in Fig. 5 for the four components of the matrix in Table 1, R_{22}, R_{23}, R_{32}, R_{33}, works as follows. **The first step [left column]**, to map the inputs into the fuzzy sets (fuzzification), gives the values of the membership functions, indicated on the plots. **The second step** [second column] is to apply the fuzzy operation AND (each cell in the table is an intersection of two fuzzy sets). On **the third step** [third column], the consequent, or THEN part of the rule, is defined as a shape of the area under the output variable membership function curve. The results are shown in the right [fourth] column in Fig. 5, where minimum is applied and a total of 3 (out of 5) curves are activated by all four rules. It is important to note that on this step the entire fuzzy set is assigned to the output variable.

In engineering applications, most often the *min* or algebraic product is used for fuzzy intersections (AND), and for fuzzy inferences. *Min* was used in the presented example. While a specific form of the FL rules was selected in Fig. 5, it is not unique (see [4] for the discussion of alternative approaches).

Every time when a rule is fired, the value of the antecedent (between 0 and 1) truncates or shapes the fuzzy set (the respective bell curve) by means of the implication operator (*min*). Two most widely used inferences are minimum and product; a minimum is used in this example. On **the fourth step**, all output fuzzy sets from the four IF-THEN rules are joined into a single output membership function by applying the aggregation operator (*maximum*). As can be seen, each fired rule contributes to the overall output. Finally, on **the fifth step** the aggregate membership function is reduced to a single value. In the example, the center of gravity of the output fuzzy set is returned (Fig. 5). The output statement is that strength of the recommendation to trim is 0.43 (on the 0 to 1 scale). This strength was compared with similar values for other elements, and a decision was made to increase Functional Significance of the tower (schematically shown by the arrow in Fig. 4).

IV. CONCLUSIONS. ADVANTAGES OF USING FL FOR DECISION MAKING WHEN SOLVING INVENTION PROBLEMS

The presented approach offers a more logical and consistent way to formalize qualitative or subjective inputs describing an invention problem and formulate a problem statement following uniform rules. The approach also provides enough flexibility for the decision maker, who can within reasonable limits modify the membership functions. E.g., if in a specific problem cost considerations are more important, the respective membership function can be adjusted to take higher values (closer to 1) at lower cost.

The approach can be easily incorporated in the decision making software. In this case, the technique can be made transparent to a user on two levels. At the first level, upon request of the user, a matrix with the "IF-THEN" rules can be shown, one plane (layer) at a time. At the second level, the specific shape of the membership functions can be shown. It should be noted that using this software will require certain discipline from those practitioners who are used to more relaxed way of thinking.

Applicability of the approach to invention problem solving is also supported by the well established features of FL algorithms (consistency, reliability, performance, transparency and flexibility), and by successful application of FL to diverse linguistically formulated problems (medical decision making, detection of hidden objects, commodity pricing, et al). This paper draws attention to the fact that invention problem solving is an application still waiting for objective, user-independent tools.

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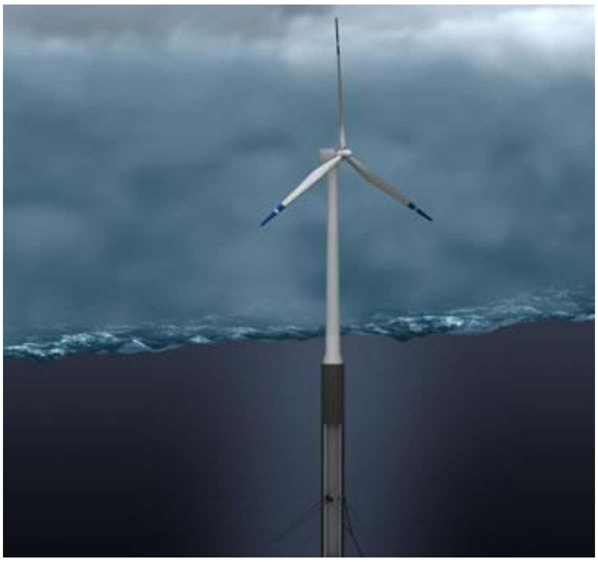

Fig. 3. An offshore floating wind tower

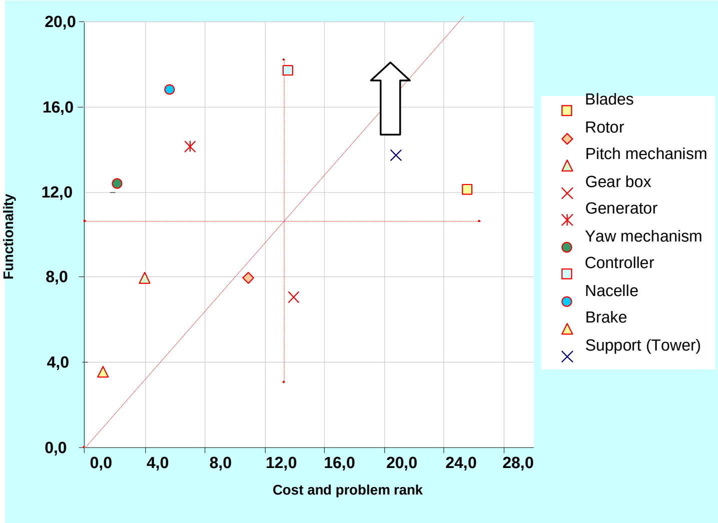

Fig. 4. Functionality and Cost & Problem Rank of a floating wind tower

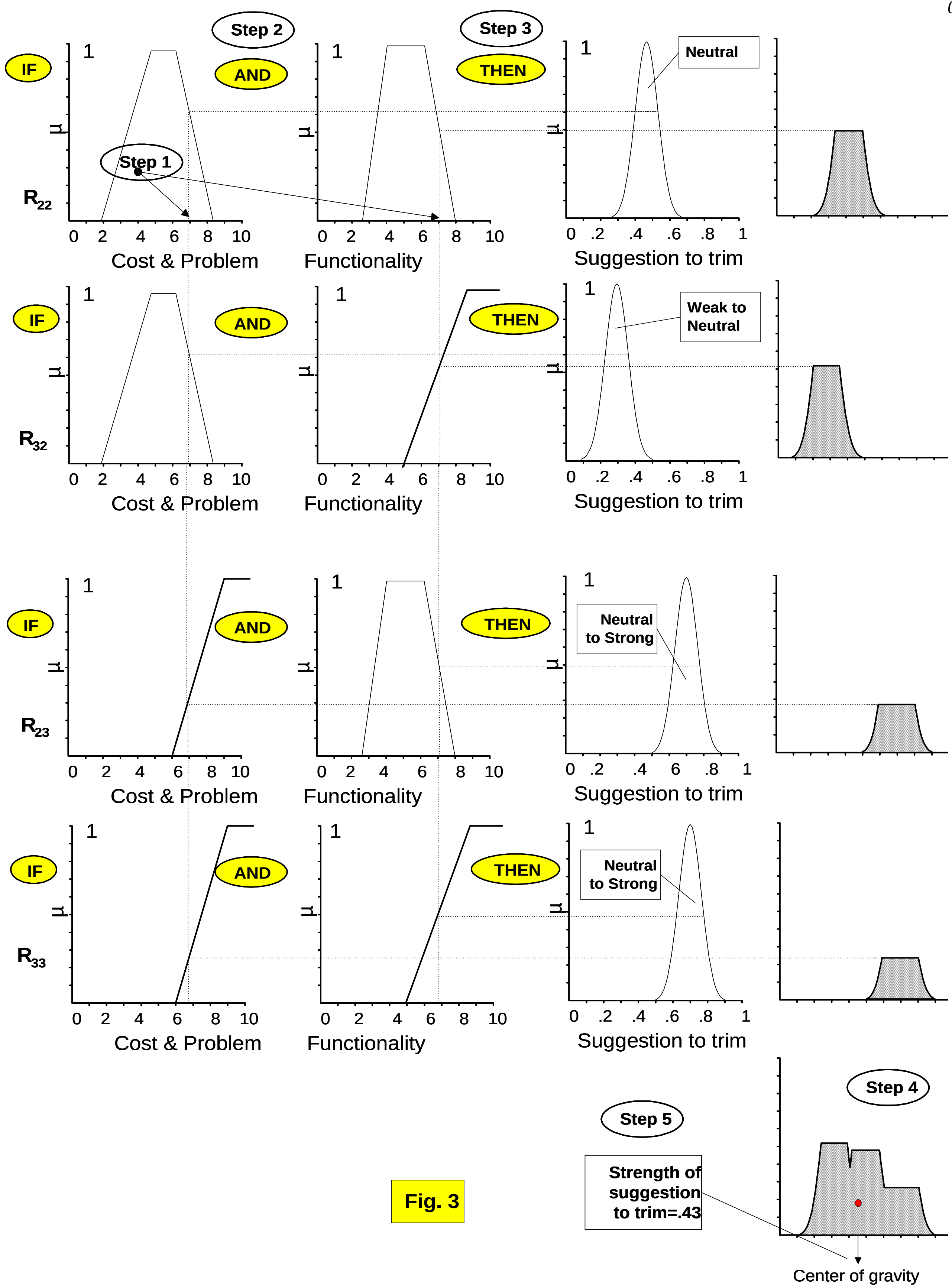

Fig. 5. Example of decision making procedure: IF functional significance=7, and trouble index=7, THEN the strength of recommendation to trim is 0.43.