Analysis of the job satisfaction index problem by using fuzzy inference

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Abstract

In this study we propose a fuzzy rule-based algorithm to evaluate job satisfaction in an organization. We collected the effective factors/job facets of job satisfaction through interviews. Through analyzing the interview results we compose fuzzy rules. By using the obtained rules, the value of job satisfaction is computed using the expert system shell ESPLAN. The basic advantage of the used approach is being able to operate with imperfect information for the evaluation of job satisfaction by using fuzzy logic.

Keywords: job satisfaction; fuzzy logic; possibility measure; expert system; fuzzy inference; Minnesota Satisfaction Questionnaire; quality measure- degree of truth

1. Introduction

There is a vast range of studies devoted to job satisfaction in the existing literature. Job satisfaction theories have a strong overlap with theories explaining human motivation. The most common and prominent theories in this area include Maslow’s Needs Hierarchy Theory1, Herzberg’s Motivator-hygiene Theory, the Job Characteristics Model2, and the Dispositional Approach3. These theories are popular in the literature related to human motivation4,5,8. Some determinants of job satisfaction are analyzed in9,12. An effective approach to job satisfaction is described. Job satisfaction indicators and their features are described in14.

Job satisfaction is not only about how much an employee enjoys work. Taber and Alliger15 analyzed other types of measures such as level of concentration required for the job, level of supervision, and task importance. This study demonstrates that the accumulating enjoyment of work tasks add up to an overall job satisfaction.

Some factors of job satisfaction may be ranked as more important than others, depending on each worker’s needs and personal and professional goals. To create a benchmark for measuring and ultimately creating job satisfaction, managers in an organization can employ proven test methods such as the Job Descriptive Index (JDI) or the Minnesota Satisfaction Questionnaire (MSQ)16. These assessments help management define job satisfaction adequately.

Five important factors/job facets can be used to measure and influence job satisfaction in the test methods17:
1. Pay or total compensation
2. The work itself (i.e., job specifics such as projects, responsibilities)
3. Promotion opportunities (i.e., expanded responsibilities, more prestigious title)
4. Relationship with supervisor
5. Interaction and work relationship with coworkers.

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In the authors propose a fuzzy rule-based algorithm to evaluate the job satisfaction in an organization. First, they collect the effective factors/job facets of job satisfaction through interviews. After analyzing the interview results, they propose questionnaires with respect to categories obtained from interviews. Due to qualitative aspect of satisfaction, they use linguistic choices in the questionnaires. While it is hard to disseminate questionnaires to all employees, sampling is performed based on STRATA technique. The results are used to compose fuzzy rules. After defuzzification of the rules and computing the distance from ideal status, the gaps are determined. The gaps are fulfilled using improvement strategies. Next, they give a brief description of STRATA sampling technique and fuzzy logic. Fuzzy logic is capable of treating this dynamic performance criterion in the uncertain and qualitative environment.

Authors examine how individuals “determine” their job satisfaction based on changes in situational factors. A simulation model, using fuzzy set theory and system dynamics, is used. As Piegat stated “information obtained from people is usually of less precision (large granularity), while information delivered by measuring devices is of higher precision (small granularity)”. For the model, the required information is obtained from people. It measures subjective features of work, consequently making fuzzy set theory a highly applicable technique to evaluate the features. The estimation of an individual’s input-output ratio and the impacts of the input-output ratio on changes to the individual’s satisfaction level are evaluated using fuzzy set theory. Fuzzy logic is used to get an approximate answer when no exact answer is possible.

The purpose of this study is to determine the level of employee job satisfaction through the use of the Minnesota Satisfaction Questionnaire (MSQ) based production rules and the fuzzy expert system shell ESPLAN. The paper is organized as follows. Section 2 discusses the description of fuzzy if-then rules and fuzzy inference algorithm. The statement of the problem is described in section 3. Theresults of computer simulation are described in Section 4 and Section 5 concludes the study.

2. Description of fuzzy if-then rules and fuzzy inference algorithm

Knowledge in if-then rules based systems can be described in different ways. Some of the post-modern techniques for representation of knowledge include logical calculus and a structured model. This work is devoted to the rule-based system oriented approaches of knowledge representation. A rule-based system consists of three main parts: 1) a set of if-then rules, 2) dynamic database, called the working-storage, 3) control interpreter, which interprets the database using the set of rules. The rule-based system has a wide class of applications in decision making problems, planning problems, business problems, technical problems, and in social sciences such as psychology and medicine.

The shell of ESPLAN provides the following basic abilities: development of expert systems for various applications; building module-oriented structures and knowledge bases; segmentation; representation of fuzzy values; compositional inference with possibilistic measures; arithmetic operations with fuzzy numbers; realization of simple user-machine dialogue (execution of queries) by using special functions; the use of a confidence degree for any rule (in percent); call of external programs; data interchange using file system.

The mathematical description of knowledge in the knowledge base is based on fuzzy interpretation of antecedents and consequents in if-then rules.

For the knowledge representation the antecedent of each rule contains a conjunction of logical connectives like \[ \text{linguistic value} \] named elementary antecedent.

The consequent of the rule is a list of imperatives, among which may be some operator-functions (i.e. input and output of objects’ values, operations with segments of a knowledge base, etc). Each rule may be characterized with a confidence degree \( Cf \in [0,100] \).

Each linguistic value has a corresponding membership function. The subsystem of fuzzy arithmetic and linguistic values processing provides automatic interpretation of linguistic values like “approximately \( A \)”, “less than \( A \)”, “more than \( A \)”, “middle”, “much”, “high”, “low”, “near…”, “from…to….” and so on; i.e. for each linguistic value this subsystem automatically computes parameters of membership functions using universes of corresponding variable. The value of linguistic variable are trapezoidal fuzzy numbers, which is described as:

less than \( A \): \( 0, I, A - Z, Z \) approximately \( A \): \( Z, A, A, Z \) more than \( A \): \( Z, A + Z, S, 0 \)

neutral: \( Z, I, +2*Z, I + 3*Z, Z \) much: \( Z, S - Z, S, 0 \) etc.,

where \( I \) and \( S \) are respectively minimum and maximum values of universe, \( Z = (I - S)/5 \).

The user of the system may define new linguistic values, modify built-in ones and explicitly prescribe a membership function in any place where linguistic values are useful. The fuzzy if-then rules have the following form:

\[ R^k: \text{IF } x_i \text{ is } \tilde{A}_{ij} \text{ and } x_j \text{ is } \tilde{A}_{jk} \text{ and...and } x_n \text{ is } \tilde{A}_{kn} \text{ THEN } u_{i1} \text{ is } \tilde{B}_{i1} \text{ and } u_{i2} \text{ is } \tilde{B}_{i2} \text{ and...and } u_{iJ} \text{ is } \tilde{B}_{iJ}, \quad k = 1, K \]

where \( x_i, x_j, ..., x_n \) are total input and local output variables, \( \tilde{A}_{ij}, \tilde{B}_{ij} \) are fuzzy sets, and \( k \) is the number of rules. Note, that inputs \( x_1, x_2, ..., x_n \) may be crisp or fuzzy variables.

Efficiency of the inference engine considerably depends on the knowledge base internal structure. The inference mechanism acts as follows. First, current values of objects are given (initial data). Then all rules antecedents of which overlap with these current values are chosen from the knowledge base. For these rules, the truth degrees of the rules are computed (in other words,
the system estimates the truth degree of the fact that current values of objects correspond to values fixed in antecedents). If the
truth degree exceeds some threshold then imperatives from consequents of a rule are executed. The assigned value of the object
is also complemented by a numeric confidence degree.

A truth degree of a rule’s antecedent is calculated according to the following algorithm\(^\text{21}\):

1. First the objects are evaluated, i.e. every \(w_i\) object has appropriate value defined as \((v_i, cf_i)\), where \(v_i\) is linguistic value,
\(cf \in [0, 1000]\) is confidence degree of the value \(v_i\). Then it is needed to compute:

\[
 r_j = \text{Poss} \left( \tilde{\alpha}_j / \tilde{\alpha}_j \right) \cdot cf_j, \quad \text{if the sign is “=” or } r_j = \left( 1 - \text{Poss} \left( \tilde{\alpha}_j / \tilde{\alpha}_j \right) \right) \cdot cf_j, \quad \text{if the sign is “≠”}
\]

\(Poss\) is defined as:

\[
 \text{Poss} (v / \tilde{\alpha}) = \max_{u} \min \left( \mu_{\tilde{\alpha}} (u), \mu_{\tilde{\alpha}} (u) \right) \in [0,1] \quad r_j = \min \left( r_j \right)
\]

\(\alpha_i\) - current linguistic value (j is index of the rule, k is index of fuzzy relation)

2. For each rule, calculate \(R_j = \left( \min_{j} r_j \right) \ast CF_j / 100\),
where CF is the confidence degree of the rule\(^\text{21}\).

The user or the creator of the rule defines the firing level \(\pi\) and \(R_j \geq \pi\) is checked. If the condition holds true, then the
consequent part of rule is calculated.

3. The evaluated \(w_i\) objects have \(S_i\) values\(^\text{21}\): \(w_i, (v'_i, cf'_i), \ldots, (v'_i, cf'_i)\)

The consequents of rules are aggregated into the average\(^\text{21}\):

\[
 v_i = \frac{\sum_{k=1}^{S_i} v'_i \cdot cf'_i}{\sum_{k=1}^{S_i} cf'_i}
\]

IF \(x_1 = \tilde{a}_1^j \text{ AND } x_2 = \tilde{a}_2^j \text{ AND } \ldots \text{ THEN } y_1 = \tilde{b}_1^j \text{ AND } y_2 = \tilde{b}_2^j \text{ AND} \ldots\)

IF ... THEN \(Y_1 = \text{AVRG} (y_1) \text{ AND } Y_2 = \text{AVRG} (y_2) \text{ AND} \ldots\)

This model has a built-in function \(\text{AVRG}\) which calculates the average value. This function simplifies the implementation of
compositional inference with possibility measures. As a possibility measure, here a confidence degree is used. So, the
compositional relation is given as a set of rules like

IF \(x_1 = \tilde{A}_1^j \text{ AND } x_2 = \tilde{A}_2^j \ldots \text{ THEN } y_1 = \tilde{B}_1^j \text{ AND } y_2 = \tilde{B}_2^j \text{ AND} \ldots\)

where \(j\) is a number of a rule. After all these rules have been executed (with different truth degrees) the next rule (rules) ought to
be executed:

IF THEN \(Y_1 = \text{AVRG} (y_1) \text{ AND } Y_2 = \text{AVRG} (y_2) \text{ AND} \ldots\)

Using this model one may construct hypotheses. Such system contains the rules:

IF \(<\text{condition}, > \text{THEN } X = \tilde{A}_j \text{ CONFIDENCE } cf_j\)

Here ”\(X = \tilde{A}_j\)” is a hypothesis that the object \(X\) takes the value \(\tilde{A}_j\). Using some preliminary information, this system
generates elements \(X = \left( \tilde{A}_j, R_j \right)\), where \(R_j\) is a truth degree of \(j\)-th rule. In order to account the hypothesis (i.e. to estimate
the truth degree that \(X\) takes the value \(A_j\) the recurrent Bayes-Shortliffe formula\(\) generalized for the case of fuzzy hypotheses, is
used\(^\text{21}\):

\[
P_0 = 0
\]

\[
P_j = P_{j-1} + cf_j \cdot \text{Poss} \left( \tilde{A}_j / \tilde{A} \right) \left( 1 - \frac{P_{j+1}}{100} \right)
\]
This formula is realized as a built-in function $BS(u) :IF \ END \ THEN \ P = BS \left( X, \hat{A}_y \right)$.

3. Statement of the problem

Defining overall job satisfaction is a very important problem. The basic problem is to evaluate overall satisfaction of respondents by using job facets. For determining overall satisfaction from evaluation of job facets, we use fuzzy rules. The overall job satisfaction denoted $y$ is a compound index built from twenty components each of which is assessed by an expert judgement. The twenty components are: $x_1:$ Activity, $x_2:$ Independence, $x_3:$ Variety, $x_4:$ Social status, $x_5:$ Supervision–human relations, $x_6:$ Supervision–technical, $x_7:$ Moral values, $x_8:$ Security, $x_9:$ Social service, $x_{10}$: Authority, $x_{11}$: Ability, $x_{12}$: Company policies and practices, $x_{13}$: Compensation, $x_{14}$: Advancement, $x_{15}$: Responsibility, $x_{16}$: Creativity, $x_{17}$: Working conditions, $x_{18}$: Co-workers, $x_{19}$: Recognition, $x_{20}$: Achievement.

Using the above mentioned parameters, the overall job satisfaction model can be expressed as:

IF $x_1 =$ "very satisfied" AND $x_2 =$ "very satisfied" AND $x_3 =$ "very satisfied" AND $x_4 =$ "less satisfied" AND $x_5 =$ "quite satisfied" AND $x_6 =$ "quite satisfied" AND $x_7 =$ "very satisfied" AND $x_8 =$ "composition" AND $x_9 =$ "very satisfied" AND $x_{10}$ = "satisfied" AND $x_{11}$ = "very satisfied" AND $x_{12}$ = "satisfied" AND $x_{13}$ = "very satisfied" AND $x_{14}$ = "very satisfied" AND $x_{15}$ = "very satisfied" AND $x_{16}$ = "very satisfied" AND $x_{17}$ = "very satisfied" AND $x_{18}$ = "quite satisfied" AND $x_{19}$ = "satisfied" AND $x_{20}$ = "very satisfied" THEN $y$ = "satisfied";

IF $x_1 =$ "very satisfied" AND $x_2 =$ "satisfied" AND $x_3 =$ "very satisfied" AND $x_4 =$ "very satisfied" AND $x_5 =$ "very satisfied" AND $x_6 =$ "satisfied" AND $x_7 =$ "very satisfied" AND $x_8 =$ "satisfied" AND $x_9 =$ "satisfied" AND $x_{10}$ = "satisfied" AND $x_{11}$ = "very satisfied" AND $x_{12}$ = "satisfied" AND $x_{13}$ = "very satisfied" AND $x_{14}$ = "very satisfied" AND $x_{15}$ = "very satisfied" AND $x_{16}$ = "very satisfied" AND $x_{17}$ = "satisfied" AND $x_{18}$ = "quite satisfied" AND $x_{19}$ = "satisfied" AND $x_{20}$ = "very satisfied" THEN $y$ = "satisfied";

... (2)

IF $x_1 =$ "quite satisfied" AND $x_2 =$ "quite satisfied" AND $x_3 =$ "quite satisfied" AND $x_4 =$ "satisfied" AND $x_5 =$ "satisfied" AND $x_6 =$ "satisfied" AND $x_7 =$ "satisfied" AND $x_8 =$ "satisfied" AND $x_9 =$ "satisfied" AND $x_{10}$ = "satisfied" AND $x_{11}$ = "quite satisfied" AND $x_{12}$ = "less satisfied" AND $x_{13}$ = "less satisfied" AND $x_{14}$ = "quite satisfied" AND $x_{15}$ = "satisfied" AND $x_{16}$ = "quite satisfied" AND $x_{17}$ = "less satisfied" AND $x_{18}$ = "satisfied" AND $x_{19}$ = "quite satisfied" AND $x_{20}$ = "quite satisfied" THEN $y$ = "satisfied".

These rules have been extracted from experts’ knowledge based on interviews conducted by us. The trapezoidal fuzzy numbers describing the used linguistic terms are given below:

unsatisfied or less than $A$, (0, I, A - Z, Z); less satisfied or approximately $A$, (Z, A, A, Z); very satisfied or more than $a =$ (Z, A + Z, S, 0); quite satisfied or neutral = (Z, I, + 2 * Z, I + 3 * Z, Z); satisfied or much = (Z, S - Z, S, 0)

where I and S- respectively minimum and maximum value of universe, $Z = (S - I)/5$. Graphical representation of the trapezoidal fuzzy numbers is given in Fig. 1.

![Fig. 1 Linguistic terms for “job satisfaction”](image-url)

In the expert system shell ESPLAN other linguistic terms can be used such as few, average, more than $A$, less than $A$, approximately $A$, from $A$ to $B$, strict more than $A$, strict less than $A$ and etc. For every linguistic value, ESPLAN...
automatically calculates fuzzy number by using the universe. For instance, object= “activity”, I=minimum=1, S=maximum=5, linguistic term=”quite satisfied”; \( quite \text{ satisfied} \text{ or neutral} : (Z, I + 2*Z, I + 3*Z, Z) \)

Our aim is to define the level of overall job satisfaction level using twenty job facets represented by fuzzy linguistic terms.

4. Computer simulation

The above mentioned model is implemented by using the fuzzy expert system ESPLAN and different tests are performed. Different current information in tests is used.

Test 1: IF \( x_1 \) is quite satisfied AND \( x_2 \) is quite satisfied AND \( x_3 \) is less satisfied AND \( x_4 \) is less satisfied AND \( x_5 \) is unsatisfied AND \( x_6 \) is unsatisfied AND \( x_7 \) is satisfied AND \( x_8 \) is quite satisfied AND \( x_9 \) is less satisfied AND \( x_{10} \) is quite satisfied AND \( x_{11} \) is less satisfied AND \( x_{12} \) is quite satisfied AND \( x_{13} \) is quite satisfied AND \( x_{14} \) is quite satisfied AND \( x_{15} \) is unsatisfied AND \( x_{16} \) is less satisfied AND \( x_{17} \) is quite satisfied AND \( x_{18} \) is very satisfied AND \( x_{19} \) is very satisfied AND \( x_{20} \) is satisfied THEN overall job satisfaction=?

Test 2: IF \( x_1 \) is satisfied AND \( x_2 \) is quite satisfied AND \( x_3 \) is satisfied AND \( x_4 \) is less satisfied AND \( x_5 \) is quite satisfied AND \( x_6 \) is very satisfied AND \( x_7 \) is satisfied AND \( x_8 \) is quite satisfied AND \( x_9 \) is quite satisfied AND \( x_{10} \) is satisfied AND \( x_{11} \) is quite satisfied AND \( x_{12} \) is satisfied AND \( x_{13} \) is quite satisfied AND \( x_{14} \) is quite satisfied AND \( x_{15} \) is quite satisfied AND \( x_{16} \) is satisfied AND \( x_{17} \) is satisfied AND \( x_{18} \) is quite satisfied AND \( x_{19} \) is quite satisfied AND \( x_{20} \) is quite satisfied THEN overall job satisfaction=?

Test 3: IF \( x_1 \) is satisfied AND \( x_2 \) is very satisfied AND \( x_3 \) is quite satisfied AND \( x_4 \) is very satisfied AND \( x_5 \) is satisfied AND \( x_6 \) is satisfied AND \( x_7 \) is satisfied AND \( x_8 \) is satisfied AND \( x_9 \) is satisfied AND \( x_{10} \) is very satisfied AND \( x_{11} \) is satisfied AND \( x_{12} \) is quite satisfied AND \( x_{13} \) is satisfied AND \( x_{14} \) is very satisfied AND \( x_{15} \) is satisfied AND \( x_{16} \) is quite satisfied AND \( x_{17} \) is satisfaction AND \( x_{18} \) is quite satisfied AND \( x_{19} \) is satisfied AND \( x_{20} \) is satisfied THEN overall job satisfaction=?

FOR TEST1.

ANSWER:

EXPERT system shell ESPLAN’s decision is “Overall job satisfaction is LESS SATISFIED”

FOR TEST2.

ANSWER:

EXPERT system shell ESPLAN’s decision is “Overall job satisfaction is QUITE SATISFIED”

FOR TEST3.

ANSWER:

EXPERT system shell ESPLAN’s decision is “Overall job satisfaction is SATISFIED”

Fragment of computer simulation is given below.

Activity=Quite satisfied
Independence=Quite satisfied
Variety=Less satisfied
Social status=Less satisfied
Supervision-human relations=Unsatisfied
Supervision-technical=Unsatisfied
Moral values=Satisfied
Security=Quite satisfied
Social service=Less satisfied
Authority=Quite satisfied
Ability=Less satisfied
Company policies and practices= Quite satisfied
Compensation= Quite satisfied
Advancement= Quite satisfied
Responsibility=Unsatisfied
Creativity=Less satisfied
Working conditions=Quite satisfied
Co-workers=Very satisfied
Recognition=Very satisfied
Achievement=Satisfied
OVERALL JOB SATISFACTION is LESS THAN SATISFIED

5. Conclusion

In this paper for the evaluation of an overall job satisfaction index a fuzzy rule-base method is used. By using the Minnesota Satisfaction Questionnaire, values of basic determinants of respondents were determined. The fuzzy rules extracted by using interviews were performed in the expert system shell ESPLAN and different tests were performed. The obtained results of job satisfaction evaluation on the bases of real data show validity and efficiency of the suggested approach.

References