Capability Evaluation of STPs via Hybrid Heuristic Techniques

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Abstract

This paper proposes a generic technique for the evaluation and comparison of the capability of STPs as decision-making aid. The major issue in this area is conducted by comparing and evaluating success factors and the risks associated with each STPs. In this regards decision-making modelling concepts are based on the identification of capability factors and finding mathematical models to describe or to prescribe best choice. The techniques utilize a combination of subjective and qualitative assumptions and mathematical modelling techniques.

Keywords: STPs Capability Evaluation, Multiple Criteria Decision Making, Fuzzy Logic.

1. Introduction

Science and Technology Parks (STPs) tend to occupy the middle ground between research and business activities. Typically they accommodate a collection of technology-intensive companies, research institutions, and providers of technical as well as market support services. STPs bring together knowledge and business assets to exploit the commercial opportunities presented by key changes in technology and/or markets.

This paper proposes a hybrid heuristic technique (HHT) for capability evaluation and comparison of STPs. The major issues in this era can be conducted by comparing and evaluating success factors associated with their risks. In this regards decision-making concepts are based on the identification of capability factors while introducing mathematical models. The proposed technique utilizes a combination of subjective and qualitative assumptions in order to present a decision support modelling.

This approach adopts a methodical and simple criterion to system analysis from different perspectives. By introducing capability indices, the model uses established algorithms to address a particular issue, the so-called, STPs capability assessment. Capability indices proposed in this paper are the product of utilizing fuzzy relations and analytic hierarchy process (AHP) techniques. Fuzzy relation is adopted to create a common quantitative measure to relate various factors and STPs relational concept of "capable". AHP technique is adopted to define a pair-wise comparison of different factors. This technique is implemented to assign weights to each factor based on the relative levels of importance for each factor in comparison with the others. Capability factors may vary due to the nature of the each system; the methodology discussed in this paper will be sufficiently flexible to accommodate systems' diversity. A case study is introduced to illustrate the effectiveness of the proposed approach.

2. System Capability Evaluation (SCE) of STPs

To date SC has generally been assessed and analysed based on subjective assumptions. Qualitative attributes such as: reputation, collaborations, knowledge, success in delivering final aims, and technical ability coupled with some qualitative attributes i.e. volume of activities, investment, and other measurable attributes play important role in this assessment. Non-standard linguistic characteristics attributed to systems by systems' analysts have left key decision makers exposed to misjudgements with devastating consequences. Hence a platform of some sort for standardisation of the evaluation technique is required. Constituent elements of evaluation and the mathematical model to quantify the qualitative and linguistic characteristics of systems capability seems to be necessary.

Previously, researchers and practitioners developed mathematical models and algorithms for optimisation (e.g. OR Techniques) and performance measurement (e.g. Simulation) to perform systems analysis. Internal and external constituents of systems reflect the capability of STPs, while financial, and commercial issues can also take advantage of such assessment. It is for the beneficial of all participants concerning companies stayed at STPs. The stakes will always be high for key decision makers to award projects, pursue company merge, realise real market value, assess stock value, and invest on specific technology. Often qualitative judgements for SCE are based on individual experiences and knowledge. The proposed technique in this paper will utilise a systems engineering approach to offer a tool to assist decision makers to quantify such qualitative judgements. It will not completely replace knowledge-based judgements but it will offer a platform for a more robust and sound system analysis, while it uses expert system criteria. It may be argued that the best way to measure capability is to study the degree of success of delivering final result; true. However, measuring *capability* where is often being wrongly used as synonymous with *performance* may not only be measured by the final result. In addition to constituent elements of a system, capability evaluation technique (CET) will consider the ability to deliver the final outcome as a feature. Measurement factors may vary due to the nature of the system but a generic algorithm will be introduced that can be flexible enough to accommodate the diversity of systems. A study is presented to illustrate the potential of the proposed approach, while the novelty of proposed evaluation technique can be based upon methodical and simple criterion to systems analysis from different perspectives.

2.1 Problem definition

Capability of an STP may be considered as a function of qualitative and quantitative variables, those can be listed as: stationary resources (i.e. equipment /machinery/human resources), capital, investment, internal settled companies, R&D institutes, interdisciplinary collaborations as well as collaborations with other STPs, and degree of success in delivering final outcomes. For modelling simplification, this paper deals with the minimum requirements to determine the system capability (SC) among different agents that can be defined by equation 1.

$$SC_i = f(x_i^j) \qquad (1)$$

Where: SC_i : system capability for *ith* STP and x_i^j : *jth* element of the *ith* STP

In order to quantify qualitative elements crisp and fuzzy variables can be assigned. With regards to establish a fuzzy decision-making process, it is necessary to fuzzyfy the quantifiable elements. This can be achieved by defining the suitable membership functions, in which these functions should consider the properties and behaviour of respected variables. In the following section, a background to fuzzy sets is discussed.

2.2. Methodology

The proposed technique for evaluation of systems' capability and comparison will include Fuzzy Sets Theory (FST) and Analytic Hierarchy Process (AHP) procedures. CET being designed as a transparent strategic management decision support system adopts:

- FST to conform to mainly qualitative nature of decisions factors.
- AHP for its special structure of intuitive way of problem solving and its novelty in handling Multiple Criteria Decision Making (MCDM) procedures.

2.3. Fuzzy sets

According to fuzzy set theory, each object x in a fuzzy set X is given a membership value using a membership function denoted by $\mu(x)$ which corresponds to the characteristic function of the crisp set where the values range between zero and one.

2.4. Membership function and membership degree

Membership functions can be mathematically described as linear or non-linear functions. A well-behaved membership function needs to be assigned for each fuzzyfied element. In most cases, linear membership functions are sufficient to explain the behaviour of the related value of elements. For example, the higher the number of registered patents for a specific technology, the more capable that system is in that technology. In cases where a linear membership function cannot satisfy the functional behaviour of the elements, a non-linear membership function is required. For example, by recruiting a number of scientists in a lab the capability of the lab may increase exponentially. However, if the lab is flooded with scientists the capability will not continue to improve with the same rate and it may even suffer setbacks i.e. saturation**.**

2.5. Fuzzy Multi Objective Decision

Fuzzy Multi Objective Decision (FMOD) can be mathematically simulated and analysed using fuzzy rules. FMOD can be defined as a combination of Fuzzy Sets, levels of importance of decision variables, and unequal importance levels of objectives and constraints. The proposed method utilises FMOD techniques to optimise an objective function with respect to constraints.

3. Mathematical Modelling

A fuzzy decision problem, $D(x)$, can be defined as a set of N_o objectives and N_c constraints with the intent to select the best alternative from a set of X possible alternatives. The level of satisfaction by x for given criteria can be described as $\mu_i(x) \in [0,1]$. In order to determine the level to which x satisfies all criteria denoted by $D(x)$, the following statements could be made:

1. The fuzzy objective *O* is a fuzzy set on *X* characterised by its membership function:

$$\mu_O(x) : X \rightarrow [0,1] \qquad (2)$$

2. The fuzzy constraint C is a fuzzy set on X characterised by its membership function:

$$\mu_C(x) : X \rightarrow [0,1] \qquad (3)$$

3. The fuzzy decision D, must be satisfied by a combination of fuzzy objectives and fuzzy constraints.

The following section will discuss how equal or unequal levels of importance of goals and constraints can be applied to the proposed FMOD.

3.1. Goals and constraints with equal importance

If the goals and constraints are of equal importance, x is desired where mathematical relationships (4) or (5) are satisfied:

$$\begin{cases} O_1(x) \,\&\, O_2(x) \,\&\, O_3(x) \,\&\, ...O_{N_O}(x) \\ \quad\quad and \\ C_1(x) \,\&\, C_2(x) \,\&\, C_3(x) \,\&\, ...C_{N_C}(x) \end{cases} \quad (4)$$

$$D(x) = O_1(x) \cap O_2(x) \cap ......\cap O_{N_O}(x) \cap C_1(x) \cap C_2(x) \cap .....\cap C_{N_C}(x) \quad (5)$$

Where:

$N_O(x)$: Number of objectives.

$N_C(x)$: Number of constraints.

$O_i(x)$: Fuzzy value of the *ith* objective for alternative *x*.

$C_i(x)$: Fuzzy value associated with satisfaction of the *ith* constraints by alternative *x*.

The fuzzy decision in this case is characterised by its membership function:

$$\mu_D(x) = \min\{\mu_O(x) \quad , \quad \mu_C(x)\} \quad (6)$$

The best alternative x_{opt} can be determined by:

$$D(x_{opt}) = \max_{x \in X}(D(x)) \quad (7)$$

Where x_{opt} satisfies:

$$\begin{aligned} \max_{x \in X} \mu_D(x) &= \max_{x \in X}(\min\{\mu_O(x) \quad , \quad \mu_C(x)\}) \\ &= \max_{x \in X}(\min\{\mu_{O_1}(x),..., \mu_{O_{N_o}}(x) \quad , \quad \mu_{C_1}(x),...., \mu_{c_{Nc}}(x)\}) \end{aligned} \quad (8)$$

3.2 Goal and constraints with unequal importance

In cases where objectives and constraints are of unequal importance, the decision- making equations should be modified. This is to ensure that alternatives with higher levels of importance and consequently higher memberships are more likely to be selected. The positive impact of the levels of importance, w_i on fuzzy set memberships is applied through the proposed criteria. The means to this effect can be realised by associating higher values of $\boldsymbol{w_i}$ to objectives and constraints, for example the more important the alternative the higher the value associated with it.

$$D(x) = O^w(x) \cap C^w(x) \quad (9)$$

Where, $w = [w_1, w_2 ..., w_i, ...]$

$$D(x) = \min\{O^w(x) \quad , \quad C^w(x)\} \quad (10)$$

Where X_{opt} should satisfy:

$$\max_{x\in X} \mu_D^w(x) = \max_{x\in X} (\min\{\mu_O^w(x) \quad , \quad \mu_C^w(x)\}) \tag{11}$$

This can be expressed as:

$$x_{opt} = \arg\left\{\max_{x\in X} \mu_D^w(x)\right\} \tag{12}$$

$$x_{opt} = \arg\left\{\max_{x\in X} (\min\left\{\mu_{O_1}^{w_1}(x), \mu_{O_2}^{w_2}(x), ..., \mu_{O_{No}}^{w_{No}}(x), \mu_{C_1}^{w_{No+1}}(x), \mu_{C_2}^{w_{NO+2}}(x), ..., \mu_{O_{No}}^{w_{No+Nc}}(x)\right\})\right\} \tag{13}$$

3.3. Calculation of weighing numbers using AHP

Analytical Hierarchy Process (AHP) is a method used to support complex decision-making process by converting qualitative values to numerical values. AHP's main concept of priority can be defined as the *level of strength* of one alternative relative to another. This method assists a decision-maker to build a positive reciprocal matrix of pair-wise comparison of alternatives for each criterion. A vector of priority can be computed from the eigenvector of each matrix. The sum of all vectors of priorities forms a matrix of alternative evaluation. The final vector of priorities can be calculated by multiplying the criteria weighted vector by the matrix of alternative evaluation. The best alternative has the higher priority value. CET algorithm evaluates the relative importance of the decision variables using a pair-wise comparison matrix. The relative importance of each objective or constraints can be obtained using paired comparison of the elements taken two at a time. This method can be used to obtain the exponential weighing values that properly reflect the relative importance of the objective criteria and constraints concerning a decision problem. For the purpose of decision-making under variable importance, the paired comparison matrix P with the following properties is performed:

- A square matrix of order equal to the sum of the number of objectives and the number of constraints.
- The diagonal elements are 1.
- $P_{ij} = \frac{1}{P_{ji}}$ (14)
- The off-diagonal elements are specified by looking at the table of importance scale. For example, if object i is less important than object j then $P_{ji} = 3$, while if it is absolutely more important, then $P_{ji} = 9$, and so on.

To compare a set of N objects in pairs according to their relative weights, the pair-wise comparison matrix can be expressed as:

$$P = [p_{ij}] = \left[\frac{w_i}{w_j} \quad i = 1,2,...N \quad j = 1,2,...N\right] \tag{15}$$

Where $\frac{w_i}{w_j}$ refers to the *ijth* entry of P which indicates how element i is compared to element j. In order to find the vector of weights $W = [w_1 \quad w_2 \quad ....w_N]^T$, we multiply matrix P by the vector W to get: $PW = \left[\frac{w_i}{w_j}\right][w_i] = \left[\sum_{i=1}^{N} w_i\right] = N[w_i] \quad \therefore \; PW = NW \;\&\; (P - NI) = 0$ (16)

In the above calculations if P is consistent, all eigenvalues are zero except a nonzero eigenvalue referred to λ_{max} which is equal to N (the number of objects). The estimated weights can be found by normalizing the eigenvector corresponding to the largest eigenvalue.

4. Simulation Studies

An entity wishes to identify potential of collaborators to consolidate its general based operations. The entity will use CET to assess and compare some nominated potential partner's capability. Based on the results an STP with highest capability will be selected for strategic alliance. The proposed method will be implemented for study with regards to equal as well as unequal importance of objectives.

4.1. Problem Description

STPs not only have got advanced R&D facilities they also possess the state-of-the-art manufacturing technology. It is assumed that each STP is a world-class enterprise with track record of successful delivery of final product/ service. Table 1 shows four major factors that contribute to R&D activities of STPs such as: number of patents, market share percentage, and global facilities.

STPs	R&D Activities %	Number of Patents	Market Share %	Global Facilities
A	74	10	8	17
B	82	18	5	12
C	53	5	7	15
D	65	25	15	21
E	70	16	10	18

Table 1: Capability factors and their corresponding values

Linear Fuzzy function has been chosen to evaluate the degree of membership of each element to the corresponding objective function. By using equation (2) the degree of membership for each STP factor are illustrated in Table 2.

STP	$\mu_i^{R\&D}$	μ_i^{Patent}	μ_i^{Market}	$\mu_i^{Facility}$
A	0.74	0.25	0.4	0.64
B	0.82	0.65	0.25	0.18
C	0.53	0	0.35	0.45
D	0.65	1	0.75	1
E	0.7	0.55	0.5	0.72

Table 2: Degree of Membership for Capability factors

Linear fuzzy function is considered to be applicable to R&D capability, number of patents, market share percentage as well as global facilities. Since the higher the numbers the more capable the STP is in that subject area. It can be said that the highly skilled institute constitutes a major impact in STPs success, where in this regard the average percentage of success are assumed based on Table 3.

STPs	Degree of Success	$\mu_c^{Success}$
A	80%	0.92
B	85%	0.95
C	75%	0.87
D	60%	0.68
E	85%	0.95

Table 3: Average Pecentage Results of Skills

$$O(x_i) = \{(x_1, 0.92) \quad , \quad (x_2, 0.95) \quad , \quad (x_3, 0.87) \quad , \quad (x_4, 0.68) \quad , \quad (x_5, 0.95)\}$$

A sigmoid fuzzy membership function has been selected for this capability factor. It reflects the fact that at the beginning, additional success increases the capability of the system rapidly (exponentially). However, by flooding the system with scientists and highly skilled institutes the system reaches saturation. CET algorithm will run based on the two criteria: firstly, all capability factors have equal importance; secondly, those issues have unequal importance.

4.2. Example 1 – All Factors have equal importance

In this case, by using fuzzy factors the problem can be formulated as:

$$MaxF_i(x_j^i, \mu_j^i) \quad \therefore i = A, B, C, D, E \; \& \; j = 1,2,3,4,5$$

The decision function for the best alternative can be represented as:

$$D(x) = Min\left[MaxF_i(x_j^i, \mu_j^i) \quad \therefore i = A, B, C, D, E \; \& \; j = 1,2,3,4,5\right]$$

$$D(x) = \{(x_1, 0.25), \quad (x_2, 0.18), \quad (x_3, 0.00), \quad (x_4, 0.65), \quad (x_5, 0.5)\}$$

$$Opt(D(x)) \equiv Max(D(x))) \Rightarrow \text{Selected STP is D.}$$

4.3. Example 2 - Objectives and constraint are not of equal importance

Arguably, capability factors in most cases might not have equal levels of importance. This was evident when experts in the field were consulted. A pair-wise comparison matrix was defined (Equation 15) in accordance with expert input. The relationship between each member was described as:

$$P = \begin{array}{c} \\ R\&D \\ PN \\ MS \\ GF \\ S \end{array} \begin{array}{c} \begin{array}{ccccc} R\&D & PN & MS & GF & S \end{array} \\ \begin{bmatrix} 1 & 5 & 3 & 1 & \frac{1}{4} \\ \frac{1}{5} & 1 & 2 & \frac{1}{5} & \frac{1}{9} \\ \frac{1}{3} & \frac{1}{2} & 1 & \frac{1}{3} & \frac{1}{7} \\ 1 & 5 & 3 & 1 & \frac{1}{4} \\ 4 & 9 & 7 & 4 & 1 \end{bmatrix} \end{array}$$

Each value in matrix P represents the importance associated with one factor in comparison to the other. For example, comparing patent and R&D activities where R&D activities is considered to be more important than patent. Based on the AHP methodology, a value of 5 (P_{12}) is assigned to this relationship. Consequently, the inverse relation between these two factors would be $\frac{1}{5}$ (Equation 14) the maximum eigenvalue for matrix P would be λ_{max}= 5.1695 that is close to 5 which is the number of objectives. The weighting (W) vector is obtained via some matrix manipulations and it is:

$$W= [0.29741 \quad 0.094085 \quad 0.088312 \quad 0.27867 \quad 0.90401]^T$$

Using Equation (13) the final ranking of the STPs with respect to their corresponding "capability indices" are:
(E= 0.89935, A= 0.87772, D= 0.70564, B= 0.62185, C=0). $\Rightarrow$ Selected STP will be E.

4.4 Example 3 – Collaboration among STPs included

In order to complete the model the collaboration among STPs is incorporated. It seems that a left (L) and right (R) type of flat fuzzy number can demonstrate the Collaboration Fuzzy Function (CFF). L-R type fuzzy number can be defined as:

$$M = (b_i^L, b_i^R, \alpha_i, \beta_i)$$
$$\exists \quad (b_i^L, b_i^R) \in R, b_i^L < b_i^R$$
$$\mu_M(x) = 1 \; \forall \; x \in [b_i^L, b_i^R]$$

$$\mu_M(x) = \begin{cases} L(x) & a_i^L \le x_i \le b_i^L \\ 1 & b_i^L \le x_i \le b_i^R \\ R(x) & b_i^R \le x_i \le a_i^R \\ 0 & otherwise \end{cases}$$

$$L(x) = \frac{x - (b_i^L - \alpha_i)}{\alpha_i} \qquad R(x) = \frac{(b_i^R + \beta_i) - x}{\beta_i}$$

Where x_i is the level of collaboration. Parameters for fuzzy membership of collaborations are given in Table 5. The concept of a fuzzy collaboration is related to a qualitative assessment, for instance through a linguistic declaration as "collaboration *may occur between* a_i^L *and* a_i^R*, but it is more likely to be between* b_i^L *and* b_i^R". This can be translated into a trapezoidal fuzzy number as shown in Figure 1. This illustrates the fact that if levels of collaborations are less than a_i^L the corresponding membership degree will be zero. Consequently, if the levels of collaborations are greater than a_i^R then the two STPs overlap and the corresponding membership degree will also be zero.

STPs	a_i^L	b_i^L	α_i	b_i^R	a_i^R	β_i
A	0.82	0.85	0.03	0.88	0.90	0.02
B	0.75	0.81	0.05	0.82	0.85	0.03
C	0.58	0.60	0.02	0.62	0.64	0.02
D	0.80	0.83	0.03	0.86	0.88	0.02
E	0.75	0.78	0.03	0.80	0.83	0.03

Table 5: L-R fuzzy membership parameters

Collaboration fuzzy memberships (CFM) resulted from Table 5, can be viewed in Table 6.

STPs	$M(x)$	$\mu_M(x)$
A	0.84	0.67
B	0.80	0.80
C	0.63	0.50
D	0.89	0.00
E	0.81	0.67

Table 6: Collaboration fuzzy memberships

In this case it is assumed that the decision-making is under equal importance consideration for all objectives and constraints. A new decision matrix including new objective can be derived as follows:

$$D(x) = \{(x_1, 0.25),\ (x_2, 0.18),\ (x_3, 0.00),\ (x_4, 0.00),\ (x_5, 0.5)\}$$

$$Opt(D(x)) \equiv Max(D(x)) \implies \text{STP E can be selected.}$$

5. Result Analysis

Application of linear and non-linear fuzzy membership functions is exercised to contribute to the decision-making problem. In the first example, STPs D is selected due to *equal levels of importance* for all objectives/constraints. In the second example, *unequal levels of importance* for all objectives/constraints, is applied to the same case. STP E will be the nominated as the best STPs. The results in this case indicate the influence of the relative priorities given by experts to decision-making criterion. The inclusion of *collaboration* among STPs as a new decision variable is studied in the third example. A new fuzzy variable with LR membership function is introduced to reflect levels of collaborations. STP E is nominated as the most capable centre. By comparing results from example 1 and 3, it can be derived that with situation where objectives/constraints being of equal importance and incorporating the collaboration levels, Centre D is the optimal solution as opposed to Centre E. Results obtained, illustrate CET's flexibility in handling different scenarios under different conditions.

6. Conclusions

Evaluation and comparison of systems capabilities seems to be a desirable measurement tool for systems engineering and analysis. The achieved objective was to introduce a quantitative approach to address a qualitative matter. Application of a multi-objective optimisation via a heuristic technique is addressed in this paper. CET algorithm adopts fuzzy optimisation technique to evaluate and compare systems capabilities. This paper utilises the advantages of fuzzy optimisation and AHP to address multi-objective optimisation with regard to equal/un-equal levels of importance. Relative priorities are assigned to the objectives/constraints using AHP. Different case studies show the application of the proposed approach. In future other techniques such as insertion technique can be added to CET in order to reduce computational efforts. Risk factors can also be introduced as complementary parameters to improve decision-making criterion.

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