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The construction projects HSE performance evaluation considering the effect of external factors using Choquet integral, case study (an Iranian power plant construction company)

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Abstract

Nowadays, industrialization exposes the human and environment resources to serious dangers. The importance of these resources caused the HSE (health, safety and environment) to have a significant contribution in industries' evaluation, especially in construction industry. While evaluating the project's success from an HSE point of view, it is not enough to rely solely on the outputs without considering the impact of external factors affecting them. On the other hand, the variety of factors affecting HSE and their different kinds of interactions, forces us to use another aggregation operators rather than linear ones. Choquet integral (CI) is a well-known powerful aggregation operator to be used in such cases. There are different methods to define the coefficients of CI. One of the most recent and prominent methods is "the most representative capacity definition method". This paper proposes a modification to this method by improving its entropy and consequently the reliability in, as named, non-reference projects evaluation. The modified algorithm is used in evaluating the impact of external factors on HSE performance of power plant construction projects. The results show the prominence of modified algorithm's entropy compared to the original algorithm. Ultimately the external factors integrated score, which resembles the suitability of project's environment, is compared with the score defined considering output results. According to results, in some projects there is a deep gap between score of HSE output result and aggregated score of external factors. The gap of two scores potentially figures the internal organizational factors performance.

Keywords: HSE, External factors, Choquet integral, Entropy, Variance of capacity.

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1. Introduction

In all project's performance evaluation, success criteria should be distinguished from success factors. Success criteria are principles or standards for measuring success. On the other hand, factors are circumstances, facts or influences which lead projects towards success, but they are not usually considered for judgment purposes (Lim and Mohamed, 1999). In general, project's HSE performance is dependent upon historical, economical, psychological, technical, procedural, organizational, and work environment issues (Sawacha et al., 1999). In tremendous projects, such as power plant construction, the most risky processes are performed by workers. Furthermore, the power plant projects of MAPNA are distributed all over Iran and since Iran is a four-season country, the climate conditions in each part of the country varies in different seasons. These changes may impose some difficulties to project staff and threaten their safety. Additionally, working at heights, installing heavy and expensive equipment, the pollution caused by site activities or local industries, as well as the workers' attitudes, knowledge and behavior towards health and safety all affect a project's health and safety criterion (Choudhry and Fang, 2008). The environment can also be destroyed by construction activities such as the waste material released in site, and the pollution caused by various processes.

Considering the importance of human resources and the environment as necessary prerequisites of life survival on the earth, and also paying attention to the point that national construction projects will be commonly utilized for many years, and therefore their risk will be a menace during their lifecycle, it is absolutely essential to study, monitor and control the factors that affect HSE in construction projects. To fulfill this goal, team members should be well-equipped during the project's completion process in order to improve the HSE performance of the project. The HSE problems' losses are not limited to mentioned issues. Actually, they will become much aggressive by disturbing the project's time and cost estimations. Therefore, all the reasons are significant enough to consider the HSE as a performance criterion in projects evaluation.

Projects' HSE evaluation is usually accompanied with especial difficulties. Evaluators usually rely on output results when evaluating projects HSE performance. These results can be measured by variety of indices, such as accident rate and incident rate, which are negative measures, unlike other performance criteria. Furthermore, a satisfied HSE output will not ensure that the project has been performed in safe conditions (Sawacha et al., 1999); even in the presence of peril, the project team and contractors may plan the work in such a way that the project terminates with satisfactory HSE output. Moreover, it shouldn't be concluded that two projects with the same HSE output achieved the same amount of success. Actually, it makes more sense to consider a project performed in less suitable conditions, to be more successful. The HSE performance is dependent upon external and inter-organizational factors (El-Mashaleh et al., 2010). Different researchers aimed at defining these factors and analyzing their effects on HSE. Thomas Ng et al. (2005) divided the safety factors to factors in the project level and factors in the organizational level. According to that study, main factors related to the project level in order of their significance includes project management commitment; hazard management; implementation; information, training and promotion; emergency procedures; reporting, recording and investigation and safety review; and main factors related to the organization level in order of their significance were declared to be administration and management commitment; safety and health training; legislation, codes and standards; safety review; accident record selection and control of subcontractors. Sawacha et al. (1999) declared that the top five important issues found to be associated with site safety were: (1) management talk on safety, (2) provision of safety booklets, (3) provision of safety equipment, (4) providing safety environment, and (5) appointing a trained safety representative on site. Abdelhamid and Everett (2000) indicated that unsafe conditions are due to four causes: (1) Management actions/inactions, (2) unsafe acts of worker or coworker, (3) non-human-related event(s), and (4) an unsafe condition that is a natural part of the initial construction site conditions. Aksorn and Hadikusumo (2008) identified 16 critical success factors of safety and grouped them as (1) worker involvement, (2) safety prevention and control system, (3) safety arrangement, and (4) management commitment. The most significant factor was concluded to be management support. Toole (2002) mentioned lack of proper training, deficient enforcement of safety, safe equipment not provided, unsafe methods or sequencing, unsafe site conditions, not using provided safety equipment, poor attitude toward safety and isolated sudden deviation from prescribed behavior as the main causes of accidents.

Cheng et al. (2012) analyzed the impact of safety management practices (SMP) on project performance in construction industry. Three SMP categories in order of their importance were defined as follows: (1) safety management process consisting of safe inspection, safety training scheme, safe work practices, safety meeting, safety audit and safe promotion. (2) Safety management information including written safety policy, accident investigation and report, safety records, safety manual, safety checklist, accident statistical analysis and formal safety organization structure. (3) Safety management committees consisting of safety committee at the project/site level, and safety committee at the company level. Safety culture is mentioned as a vital factor affecting HSE performance in most studies, but Feng (2013) has a deeper investigation into this issue. The result of his research showed that the basic safety investments would not have a strong positive effect unless the safety culture and project hazard level are in a high level. In order to improve the safety performance, the safety culture is a supplementary factor for protecting and providing a safer environment to take effect. This issue adversely affects the HSE performance of projects in Iran. Hinze et al. (2013) used the expressions: lagging indicators and leading indicators which resemble the output results and impacting factors respectively. He declared that lagging indicators provides no information other than whatever happened in the past, so no preventive or corrective actions can be planned for improving the performance based on this kind of indicators. On the other hand, by defining appropriate leading indicators and monitoring their levels during the project's execution steps it becomes possible to predict the output results in advance, so the preventive or corrective actions can be taken when necessary. Zhou et al. (2008) defined the main causes affecting safety as: drinking habits, employee's involvement, safety attitudes, safety management systems and procedures, safety knowledge, work experience, management commitment, workmate's influences and education experience. Considering the literature review, this paper firstly defines the external factors that affect HSE performance of the MAPNA Co.'s power plant projects' HSE performance, and then categorizes them based on the stakeholder that each factor arises from.

In addition to defining appropriate factors, it's also essential to define suitable evaluation model. El-Mashaleh et al. (2010) utilized DEA to measure HSE performance of different contractors with regard to five different levels of accident as the model's output and expenses on the safety as the model's input. Relying on the results of five point likert scaled questionnaire, Zhou et al. (2008) used Bayesian network (BN) to identify the main causes affecting safety. The respondents were supposed to answer the questions in a predefined discrete scale. As a matter of fact, each respondent would answer the questions based on his own interpretation of scales, which will cast doubt on reliability of results obtained. In addition, BNs explore the cause and effect relations between factors, while in some real world cases there are various kinds of interactions other than cause and effect. Since there are different kinds of interactions between factors, rather than cause and effect relations, the methods that are reviewed are not suitable to be used in this paper. CI is a powerful aggregation operator that can consider a wider range of factors interactions as well as cause and effect relations, and this is the aggregation model used in this paper. When large-scaled problems are dealt with, CI's coefficients are mostly defined in a learning process, as will be explained in following sections.

CI has been used in various selection and ranking problems. Li et al. (2013) tried to construct an aggregation function based on WAM and OWA which can restore the preferences of tourists in selection appropriate hotel in Hong Kong considering the relevant criteria. Since none of those linear methods depict the preferences of tourists, they tried to make an aggregation function based on CI in order to consider the interactions of criteria into account. They used the software FMtools (Beliakov, 2008) to construct the measures of CI in accordance to preferences of tourists. Expectably FMtools provided measures for CI that could restore the preferences of tourists. Wu et al. (2014) used CI to select a suitable site for thermal power plant construction by means of λ-fuzzy measure. Demirel et al. (2010) used generalized CI in warehouse location selection problem. CI is also used in supply chain partner selection (Ashayeri et al., 2012), site selection in optoelectronics industry (Kuo et al., 2013), natural gas destination (Gomes et al., 2009), assessment of software quality (Pasrija et al., 2012), and human resource evaluation (Gürbüz and Albayrak, 2014).

The remainder of this paper is as follows. Section 2 contains an introduction to capacity definition methods in the order they have been proposed in the literature. Section 3 provides some basic definitions of Choquet Integral and the formula needed for this research. Then, in section 4 a modification on one of the powerful capacity definition methods, *i.e.* the most representative capacity definition method, is proposed to improve the entropy of the capacity. The modified algorithm is used for MAPNA Co.'s projects HSE evaluation in section 5 and finally section 6 is the conclusion.

2. Choquet integral

Choquet integral is a well-known fuzzy integral operator. Fuzzy integrals were introduced in Sugeno's thesis in 1974, and have being used in multi criteria decision making problems since mid-1980. Multi–criteria decision analysis (MCDA) problems associate with evaluating a set of finite alternatives $A = \{a, b, .., m\}$ with respect to a set of finite criteria$N = \{1,2, \dots, n\}$. Each alternative *a,* is associated with an n–dimensional profile $\boldsymbol{x}^a = ({x_1}^a, {x_2}^a, \dots, {x_n}^a)$ $x^a$where ${x_i}^a$ is a non–decreasing value function (also named utility function) that represents the partial score of alternative x related to criterion i. Making a suitable evaluation model for MCDM problems requires some preference relations made by DM. The comparisons should be commensurate, that's why all scores should be represented in the same interval scale, commonly [0, 1] scale (Kojadinovic, 2007, Grabisch et al., 2007).

In most cases, DMs cannot make a complete preference among alternatives, but they can make partial preferences among a subset of alternatives called reference alternatives, $A' \subseteq A$. Then, an admissible utility function $U: \mathbb{R}^n \rightarrow \mathbb{R}$ should be defined to aggregate partial scores *i.e.*, it should have the ability to restore DMs preferences. For instance, if DM indicates that alternative a is preferred to alternative b, *i.e.* $a \gtrsim b$, the admissible utility function used for aggregation should assign a value to a not smaller that the value assigned to b, equation (1). Multi–attribute utility theory (MAUT) is a well-known admissible additive aggregation method (Grabisch and Labreuche, 2010).

$$a \gtrsim b \Leftrightarrow U({x_1}^a, {x_2}^a, \dots, {x_n}^a) \geq U({x_1}^b, {x_2}^b, \dots, {x_n}^b)\,, \forall\, a, b\, \in A \tag{1}$$

The selection of aggregation function depends on the nature of problem at hand; when criteria can be assumed independent, additive models such as weighted arithmetic mean (WAM) can be used ($WAM(a) = \sum_{i=1}^{n} W_i {x_i}^a$)

In most real world situations the criteria may have some interactions among themselves (Angilella et al., 2010b). For example, considering the factors defined in this paper, there is a negative interaction (redundancy) between government agency's sensitivity to HSE problems and MAPNA's regulations. Since projects in which government agencies are more sensitive MAPNA's regulations are more strict, even if both factors be important factors, their importance when satisfied simultaneously is less than the sum of their importance when considered separately.

When the criteria have interactions, the weight vector of WAM can be replaced with a monotone *set function* μ on N called *capacity* or *fuzzy measure*. By defining a weight for each subset of criteria, it becomes possible to calculate the importance of each subset of criteria in decision problem, and consequently take the criteria interaction into account. A suitable utility function to be used when criteria interact is a generalization of WAM called discrete CI with respect to defined capacity (Grabisch, 1996, Grabisch, 1997, Grabisch, 2009, Marichal, 2000).

In order to use CI as an aggregation operator its parameters (capacity) should be clearly defined. Capacity can be defined *directly* or *indirectly*. Direct method can be used in cases where capacity is known, so the aggregated score can be calculated by defining the partial scores (traditional aggregation method). In other words, DM should define whole parameters of model which requires his/her full awareness of the problem. But in real world problems DM is not fully aware of preference relations, and cannot define all of the coefficients with high reliability. That's why the indirect methods are proposed in which DM is not constrained to make full preferences. Actually, only some preference relations are required to be used in learning process in which parameters will be induced by means of ordinal regression methodology (disaggregation approach). Then, the induced parameters can be used in evaluating whole alternative set (aggregation approach).

The method of defining parameters when aggregation model is non–additive is called *non–additive ordinal regression* (Greco et al., 2008, Angilella et al., 2010b). In this method DM should express his preferences, in form of partial preorders, on reference alternatives $\gtrsim^*$, preferences on criteria $\trianglerighteq \triangleright$ and sign of interaction indices and preferences on them $\trianglerighteq_{Int} \triangleright_{\mathrm{Int}}$ (Kojadinovic, 2007, Marichal and Roubens, 2000, Grabisch et al., 2007, Angilella et al., 2010b, Angilella et al., 2010a). DM could also express intensity of preferences between pairs of reference alternatives $\gtrsim^*$, criteria $\trianglerighteq^* \triangleright^*$ and interaction indices $\trianglerighteq^*{}_{Int}$ as defined in$\triangleright^*_{\mathrm{Int}}$ (Angilella et al., 2009, Angilella et al., 2010b).

Each capacity definition method based on optimization aims at defining a capacity that maximizes or minimizes a function with respect to constraints induced from preference relations (Labreuche, 2008, Marichal and Roubens, 2000, Grabisch et al., 2007, Kojadinovic, 2007, Beliakov, 2008, Beliakov, 2009). The major drawback of almost all methods is that selection of ultimate solution among all compatible ones is done arbitrarily. That's why they may not necessarily lead to a unique capacity that fulfills DM's preferential information. Furthermore, some methods, except those based on maximizing the entropy or minimizing the variance, lead to uneven capacity which decreases their reliability in evaluating the alternatives that aren't considered in preference relations (Grabisch et al., 2007). In addition, all methods based on optimizing an objective function (Murofushi, 1992, Kojadinovic, 2007, Labreuche, 2008, Marichal and Roubens, 2000, Beliakov, 2008, Beliakov, 2009), lead to solutions that may provide more information than whatever can be inferred from preferences of DM. This may cause the DM's confusion, and consequently him/her misinterpretation of the actual purpose of optimization model. Actually, it's much preferred to define the capacity only with respect to DM's preference relations (Labreuche, 2009). In order to overcome mentioned drawback, *Robust Ordinal Regression* is proposed which takes into account all sets of parameters (utility functions) compatible with the preferences of DM. This approach uses the primary preferential information of DM to suggest robust comparisons among alternatives, criteria, etc.

The first Robust Ordinal Regression method proposed is UTA^{GMS} (Greco et al., 2008). It uses a set of pairwise comparisons provided by DM as the preference information (Greco et al., 2008). Then by means of linear programming, two binary relations on the set A will be defined; *necessary preference relation (NPR)* which holds for any pair $a, b \in A$ if all compatible utility functions assign a value to a not smaller than the value assigned to b and *possible preference relation (PPR)* which holds for any pair $a, b \in A$ if at least one compatible utility function assigns a value to a not smaller than the value assigned to b (Angilella et al., 2010a, Angilella et al., 2010b). NPRs are robust with respect to indirect preference information because any pair of alternatives having NPR will be ranked in the same way whatever the compatible utility function (Greco et al., 2008). *Generalized Regression with Intensities of Preference (GRIP)* (Figueira et al., 2008) is the generalization of UTA^{GMS} which takes into account not only the preferences on alternatives but also intensity of preferences between pairs of alternatives (Figueira et al., 2008, Angilella et al., 2010a, Angilella et al., 2010b). Non–additive robust ordinal regression (NAROR) (Angilella et al., 2010b) is a method inspired from UTA^{GMS} and GRIP to be used whenever the utility function is CI.

The most representative utility function (Angilella et al., 2010a) utilizes NPRs and PPRs to define a utility function that demonstrates the NPRs and PPRs in the best way. The main objective of this model is to help DM to have better interpretation of results of NAROR method (Angilella et al., 2010a).This utility function is obtained by maximizing the difference between the values assigned by CI to pairs of alternatives for which there is NPR and minimizing the difference between scores of pairs for which there is not such relation (Angilella et al., 2010a).

This paper improved the most representative utility function by considering evenness property when defining a robust capacity which is representative. The proposed algorithm has been used in MAPNA MD–2's terminated projects evaluation.

Note that in this paper for the simplicity reasons the cardinality of subsets *S, T,…* will be shown by lower case letters *s, t,…* ; the accolades {} have been omitted for small cardinality subsets. For example (*N \ i*) is used instead of $(N\backslash\{i\})$, $\mathcal{P}(N)$ indicates power set of *N*, $(\mathbf{1}_A,\mathbf{0}_{N\backslash A})$ represents a binary alternative, *i.e.* an alternative that has complete satisfaction level in the criteria included in *A* and complete non–satisfaction level in remaining criteria. *E(.)* represents the expected value.

3. Basic definitions of Choquet integral

3.1. Choquet integral as an aggregation function

Definition 1 – A *capacity* on N is a set function $\mu:\mathcal{P}(N)\rightarrow[0,1]$ with $\mu(\emptyset)=0,\mu(N)=1$ (*boundary condition*), and $\forall S,T\in N, S\subseteq T\Rightarrow\mu(S)\leq\mu(T)$ (*monotonicity condition*). *Monotonicity* means that the weight of subset of criteria will not decrease by introducing a new criterion to it (Grabisch and Labreuche, 2010, Grabisch, 1996, Grabisch, 2009). $\mu(S)$ is the weight or importance of coalition *S* of criteria.

Since defining 2^n–2 parameters arises time and space complexity, in most cases k−additive capacity (Grabisch, 1997) is used which takes into account the interactions between up to k criteria, k $\in\{1, \ldots, n\}$, and decreases the number of parameters to $\sum_{i=1}^{k}\binom{n}{i}$. 2−additive capacity is the commonest capacity in MCDM field. It doesn't have space complexity and it has acceptable flexibility. The parameters to be defined for 2−additive capacity include importance of each single criterion and interaction between pairs of criteria. This kind of interaction is more comprehensible than higher order ones (Grabisch and Labreuche, 2010).

Definition 2 – The *Möbius representation* of capacity is defined by the set function; $m: 2^n\rightarrow\mathbb{R}$. Capacity could be defined in terms of Möbius representation by:

$$\mu(R)=\sum_{T\subseteq R}m(T),\forall R\subseteq N \tag{2}$$

The Möbius representation can be obtained from capacity by:

$$m(R)=\sum_{T\subseteq R}(-1)^{r-t}\mu(T),\forall R\subseteq N \tag{3}$$

Boundary and monotonicity conditions could be defined in terms of Möbius representation respectively by $in\ general$: $m(\emptyset)=0,\sum_{T\subseteq N}m(T)=1$ and, $\sum_{T\subseteq R}m(T)\geq 0,\forall R\subseteq N,\forall i\in R.$

$2-additive$: $m(\emptyset)=0,\sum_{i\in N}m(i)+\sum_{\{i,j\}\subseteq N}m(ij)=1\ \ and, m(i)\geq 0,\forall i\in N,\ m(i)+\sum_{j\in N\backslash i}m(ij)\geq 0,\forall i\in N$

Definition 3 – *The Choquet integral* (Choquet, 1953) of x with respect to capacity μ is defined by:

$$C_\mu(x)=\sum_{i=1}^{n}x_{(i)}[\mu(A_{(i)})-\mu(A_{(i+1)})]=\sum_{i=1}^{n}\mu(A_{(i)})[x_{(i)}-x_{(i-1)})]=\sum_{i=1}^{n}x_{(i)}[\mu(A_{(i)})-\mu(A_{(i+1)})] \tag{4}$$

Where $(.)$ indicate a permutation on N such that $0 \leq x_{(1)} \leq x_{(2)} \leq \cdots \leq x_{(n)} \leq 1$ and $A_{(i)} = \{(i), \ldots, (n)\}$ for all $i \in \{1, \ldots, n\}$ and $A_{(n+1)} = \emptyset$ and $x_{(0)} = 0$.

CI can be defined in terms of Möbius representation by:

$$in\ general\text{: } C_\mu(x) = \sum_{T \subseteq N} m(T) \wedge_{i \in T} x_i \tag{5}$$

$$2 - additive\text{: } C_\mu(x) = \sum_{i \in N} m(i)\, x_i + \sum_{ij \subseteq N} m(ij) min\,(x_i\,, x_j)$$

3.2. Behavioral analysis of Choquet integral

In order to have better comprehension of behavioral properties of CI, some values must be introduced. The most important of them are *Shapley value* (Shapley, 1953), interaction index or *Murofushi–Soneda interaction index* (Murofushi and Soneda, 1993) *entropy* (Kojadinovic et al., 2005, Marichal, 2002) and *variance* (Kojadinovic, 2007), which are defined as follows:

Definition 4 –The Shapley value of criterion $i \in N$ (Shapley, 1953) with respect to capacity μ is commonly used as its importance index. The formula for importance index in terms of Möbius representation is:

$$\vartheta_i = \sum_{T \subseteq N \setminus i} \frac{m(T \cup i)}{t+1} \tag{6}$$

Definition 5 – *Interaction index* between criteria *i, j* $\in N$ with respect to the value $\mu(T)$ is measured by *Murofushi–Soneda interaction index*. This index in terms of Möbius representation is as follows:

$$in\ general\text{: } I(ij) = \sum_{T \subseteq N \setminus ij} \frac{m(T \cup ij)}{t+1}, \qquad 2 - additive\text{: } I(ij) = m(ij) \tag{7}$$

If these criteria are positively correlated or *competitive* (resp. negatively correlated or *complementary*) the sign of this expression will be ≤0 (resp. ≥0). Interaction index of *i,j* is the mean value of this marginal interaction in the presence of any subset of criteria excluding *i ,j* (Marichal, 2000) .

Definition 6 – *Entropy* is a measure of uniformity or evenness of capacity. Some indices have been introduced to measure the entropy of capacity, mainly Marichal entropy $H_M(\mu)$ (Marichal, 2002) and Havrda and Charvat entropy of order β (Havrda and Charvat, 1967). The entropy calculates the average value of contribution of partial scores in calculation of aggregated value (C_μ) (Kojadinovic et al., 2005):

1. If the entropy is close to its maximum value, then all partial scores contribute almost equally in aggregated value, so the aggregation function behaves like WAM.
2. If the entropy is close to its minimum value, then one of partial scores contributes much more than the others in aggregated value so aggregation function has *disjunctive* or *conjunctive* behavior.

Since most capacity definition models are based on preference information made on reference alternatives, defining its parameters as close to WAM as possible increases its reliability in evaluating the alternatives which have not contributed in capacity definition (non–reference alternatives).

Havrda and Charvat entropy of order β is a generalization of Shannon entropy. The extension of this entropy to capacity is given by (Kojadinovic, 2007):

$$\overline{H}_{HC}^{\beta}(\mu) = \frac{1}{1-\beta}\left[\sum_{i\in N}\sum_{S\subseteq N\setminus i}\gamma_s(n)[\mu(S\cup i)-\mu(S)]^{\beta}-1\right]\ ,\ \beta>0,\ \beta\neq 1,,\ \gamma_s(n)=\frac{(n-s-1)!s!}{n!} \quad (8)$$

Definition 7– *Variance* of capacity can be defined in terms of Möbius representation by equation (12) (Kojadinovic, 2007, Marichal, 2000).

$$in\ general: \overline{V}\ (m) = \sum_{S,T\subseteq N} m(S)m(T)\frac{s+t-|S\cup T|}{(s+1)(t+1)(|S\cup T|+2)} \quad (9)$$

$$2-additive: \overline{V}\ (m) = m(i) + \sum_{j\in N\setminus i}\frac{m(ij)}{2}\ , i\in N$$

It is obvious that for any capacity μ on *N*, there is a linear relationship between Havrda and Charvat entropy of order 2 and variance of capacity (Kojadinovic, 2007):

$$\overline{H}_{HC}^{2}(\mu) = \frac{n-1}{n} - n\,\overline{V}(\mu) \quad (10)$$

So maximizing $\overline{H}_{HC}^{2}$ is equivalent to minimizing $\overline{V}(\mu)$ (Kojadinovic, 2007). In this paper variance of capacity is used as the measure of uniformity and the capacity with less variance value is much uniform.

In following sections, 2−additive fuzzy measures have been used and all formulas and equations defined so far will be used in terms of their Möbius representation.

3.3. Non–additive robust ordinal regression (NAROR)

Suppose that $E_{\varepsilon}^{A'}$ is a set of constraints inferred from preference relations and boundary and monotonicity conditions as follows (Angilella et al., 2010b):

1. $a \succsim b \Leftrightarrow C_\mu(a) \geq C_\mu(b) + \varepsilon\ , with\ \ a,b \in A'$
2. $(a,b) \succsim^{*} (c,d) \Leftrightarrow C_\mu(a) - C_\mu(b) \geq C_\mu(c) - C_\mu(d) + \varepsilon\ , with\ \ a,b,c,d \in A'$
3. $i \trianglerighteq j \Leftrightarrow \vartheta(i) \geq \vartheta(j)\ \ + \varepsilon, with\ i,j \in N$
4. $(i,j) \trianglerighteq^{*} (l,k) \Leftrightarrow \vartheta(i) - \vartheta(j) \geq \vartheta(l) - \vartheta(k) + \varepsilon\ , with\ \ i,j,l,k \in N$
5. $I_{ij} \leq -\varepsilon\ \ or\ \ I_{ij} \geq \varepsilon\ ,\ \ with\ i,j \in N$
6. $(i,j) \trianglerighteq_{Int} (l,k) \Leftrightarrow |I_{ij}| \geq |I_{kl}| + \varepsilon\ , with\ i,j,k,l \in N$
7. $[(i,j),(l,k)] \trianglerighteq_{Int}^{*} [(r,s),(t,w)] \Leftrightarrow |I_{ij}| - |I_{lk}| \geq |I_{rs}| - |I_{tw}| + \varepsilon,\ \ with\ i,j,k,l,r,s,t,w \in N$
8. $m(\emptyset) = 0\ \ , \sum_{i\in N} m(i) + \sum_{\{i,j\}\subseteq N} m(i,j) = 1$
9. $m(i) \geq 0, \forall i \in N\ , m(i) + \sum_{j\in T} m(i,j) \geq 0\ , \forall i \in N\ \ , \forall T \subseteq N\setminus i$

The preferences of DM are given by partial preorder $\gtrsim$ which can be decomposed to its asymmetric $\succ$, and symmetric part $\sim$ whose semantics are respectively (Angilella et al., 2010b, Angilella et al., 2010a):

$a \succ b \Leftrightarrow a$ is preferred to b with $a,b \in A'$

$a \sim b \Leftrightarrow a$ is indifferent to b with $a,b \in A'$

If $E_{\varepsilon}^{A'}$ be a consistent system it could lead to a set of compatible fuzzy measures, so by establishing two linear programs (LPs), *i.e.* P1 and P2, NPR ($\gtrsim^N$) and PPR($\gtrsim^P$) on alternatives can be defined as follows (Angilella et al., 2010a, Angilella et al., 2010b):

1) *Necessary preference relation NPR*: $x \gtrsim^N y$, $x,y \in A$ $x \succcurlyeq^N y, x, y \in A$ iff for all compatible fuzzy measures $C_\mu(x) \geq C_\mu(y)$.

2) *Possible preference relation PPR*: $x \succcurlyeq^P y, x, y \in A$ $x \gtrsim^P y$, $x,y \in A$ $x \succcurlyeq^N y, x, y \in A$ iff for at least one compatible fuzzy measures $C_\mu(x) \geq C_\mu(y)$.

The LPs are (Angilella et al., 2010b):

P1: max ε s.t: $E_{\varepsilon}^{A'}$ plus the constraint $C_\mu(y) \geq C_\mu(x) + \varepsilon$ $C_\mu(y) \geq C_\mu(x) + \varepsilon$

P2: max ε s.t: $E_{\varepsilon}^{A'}$ plus the constraint $C_\mu(x) \geq C_\mu(y)$

NPRs and PPRs could be defined with respect to the sign of ε in P1 and P2, respectively. If constraints of $E_{\varepsilon}^{A'}$ constitute a consistent system the following elicitations can be inferred (Angilella et al., 2010b):

1) Non–positive value for ε in P1 means that there is no compatible fuzzy measure for which $y \gtrsim^P x$ $y \succcurlyeq^P x$ so $x \gtrsim^N y$. This elicitation is derived from the property of NPR and PPR defined in (Greco et al., 2008) which indicates that for all $a,\ b \in A$ either $a \gtrsim^N b$ or $b \gtrsim^P a$ $y \succcurlyeq^P x.a \succcurlyeq^N b$
2) Positive value for ε in P2 concludes that $x \gtrsim^P y$.

3.4. Most representative capacity definition method

The most representative utility function (Angilella et al., 2010a) uses NPRs and PPRs to define a utility function that demonstrates in the best way the NPRs and PPRs with the purpose of helping DM to have a better interpretation of results of NAROR method. This utility function is obtained by maximizing the difference between the values assigned by CI to pairs of alternatives for which there is NPR and minimizing the difference between scores of pairs for which there is not such relation, the algorithm is as follows (Angilella et al., 2010a):

1. Establish the necessary and possible preference relations on the set A of alternatives.
2. Add to the set of constraints $E_{\varepsilon}^{A'}$ the constraints $C_\mu(x) \geq C_\mu(y) + \Upsilon$ for all pairs $(x, y) \in A \times A$ such that $x \gtrsim^N$ y and $y \not\gtrsim^N x$, *i.e.* $x \succ^N$ y.
3. Compute $max\ \Upsilon$.
4. Let the $max\ \Upsilon$ found in the previous point equal to Υ^* and add the constraint $\Upsilon = \Upsilon^*$ to the set of constraints of point 2.

5. For all pairs of alternatives $(x, y) \in A \times A$ such that $y \not\succsim^N x$ and $x \not\succsim^N$ y, which are the pairs of alternatives such that $y \succsim^P x$ and $x \succsim^P$ y, add the constraints $C_\mu(x) \geq C_\mu(y) + \delta$ and $C_\mu(y) \geq C_\mu(x) + \delta$ to the set of constraints of point 4.
6. Compute min δ.

Capacity definition in this algorithm is mainly based on the secondary preferences of DM (NPRs and PPRs). To clarify, according to the algorithm, the difference of preference between NPRs is maximized and the difference of preference between PPRs is minimized. Although the secondary preferences are driven from primary preferences, but not all of them contribute in this process. Therefore, some primary preferences have no role in capacity definition. In other words, capacity definition is based on obvious conclusions made from DM's preferences. In this way, the capacity is defined based on fewer constraints than when all primary and secondary preferences of DM are taken into account. Therefore, the former trend is supposed to give solution closer to extreme points than the latter. As the results in this paper show, if the difference of preference between both primary preferences and NPR is maximized, then the entropy of capacity will be improved. This approach shifts the optimum solution from extreme points to more interior points, *i.e.* the points with less variance or equivalently higher entropy of capacity.

Considering the explanations, this paper proposes a modification to the algorithm proposed in (Angilella et al., 2010a), as described in previous paragraph, by considering the entropy of capacity and subsequently improving the reliability of capacity obtained in evaluating non-reference alternatives. In other words, the algorithm uses NPRs and PPRs to find a representative capacity with evenness property among all compatible ones, in which the variance of capacity is used as a measure of evenness.

4. Modified most representative capacity definition method

The modified algorithm is as follows:

1. Get the preference information of DM as described in 0
2. Establish the system of constraints based on DM's preference relations and boundaries and monotonicity conditions.
3. Check the consistency of constraints; if the system is consistent go to step 6 else go to step 4.
4. Use the method proposed in (Koutsikouri et al., 2008) or any other method to determine all subsets of constraints with smallest cardinality that caused inconsistency and ask DM to select the subset with least importance to be revised or deleted in the next step.
5. Ask DM to revise the preference relations, then go to step 3.
6. Define the NPRs and PPRs on whole alternative set A, as defined in 0.
7. If the NPRs and PPRs are acceptable go to step 8 else go to step 5.
8. Add the set of constraints $C_\mu(x) \geq C_\mu(y) + \Upsilon$ for all couples$(x, y) \in A \times A$, such that $x \succsim^N$ y and $y \not\succsim^N$ x , *i.e.* $x \succ^N$ y, to constraints $E_\varepsilon^{A'}$.
9. Establish two LP problems Pr1 and Pr2, with the objectives *Z1=max* Υ and *Z2=max* $\varepsilon+\Upsilon$, respectively, subjected to the constraints of step 8. Calculate the variances of capacity related to these systems: V_1, V_2 respectively.

10. Define $V^*=min\ \{V_1,V_2\}$. Let's ε^* and Υ^* be respectively the value of ε and Υ in the system that leads to V^*.
11. Add the constraints $\varepsilon \geq \varepsilon^*$ and $\Upsilon \geq \Upsilon^*$ to the set of constraints of step 8.
12. Add the constraints $C_\mu(x) \geq C_\mu(y) + \delta$ and $C_\mu(y) \geq C_\mu(x) + \delta$ for each pair $(x, y) \in A \times A$ such that $y \not\succsim^N$ x and $x \not\succsim^N$ y , *i.e.* $x \succsim^P$ y and $y \succsim^P$ x, to the set of constraints of step 11.
13. Compute min δ.

As ε belongs to unit interval in constraints 3–7 of $E_\varepsilon^{A'}$, the partial scores should be translated to [0, 1] interval in order to let ε belong to unit interval in all constraints. The flowchart of the algorithm is given in Figure 2. After defining the necessary and possible preference relations, the primary algorithm proposed in (Angilella et al., 2010a) solves only problem Pr1 which aims at maximizing Υ. As Υ is a variable defined based on necessary preference relations, these relations have much more contribution than primary preferences of DM on capacity defined by Pr1. The major objective of modified algorithm is to provide a representative capacity whose definition is based not only on secondary (NPRs and PPRs) preferences of decision maker but also on his/her primary preferences through solving Pr2. This formulation causes Pr2's constraint to be at least as the number of constraints of Pr1. This property will shift the edge points of linear programming around the central part of solution space, i.e. closer to WAM, and subsequently the entropy will be higher by escaping from extreme points. As it was expectable, the constraints that are added to problem at step 11 mostly belong to Pr2. This is the process of defining a representative capacity which has also evenness property to some extent. Variance of capacity is used as the evenness index; *i.e.*, the capacity with less variance value is more even one.

5. Utilizing the modified algorithm for HSE evaluation

The modified algorithm is used to evaluate the effect of external factors on HSE performance of MAPNA-MD2 projects. MAPNA is a leading company in development and implementation of power, oil & gas and railway transportation projects and manufacturing corresponding equipment and MD-2 is one of its subsidiaries. HSE is a fundamental criterion for MAPNA Company. But till now almost all evaluations were based on output results without considering the effect of external factors on outcomes. This paper aims at filling this gap by considering both the external factors and output results in evaluation. To achieve this aim, a detailed literature survey was performed. Then, 20 hours meeting have held with participation of four experienced engineers and managers of MD-2, and the terminated power plant projects are selected for evaluation. All decisions are made based on agreement between participants in following steps:

1. First of all the factors affecting the HSE performance of projects of MAPNA MD-2, are defined considering the literature review, the peculiarities of MD-2 projects and Iran's economic, social and environmental conditions. These factors are divided to 6 subgroups: owner (G1), social, political and economic factors (G2), MAPNA (G3), contractors (G4), environment and climate related factors (G5), project characteristics (G6). Figure 1 shows the relations between categories. Each group can be considered as a stakeholder of the project.

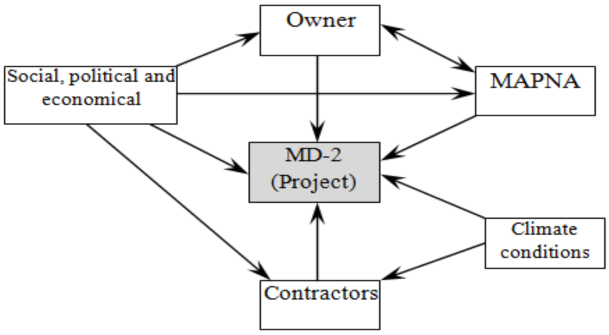

Figure 1. The relationship between MD-2 projects' stakeholders

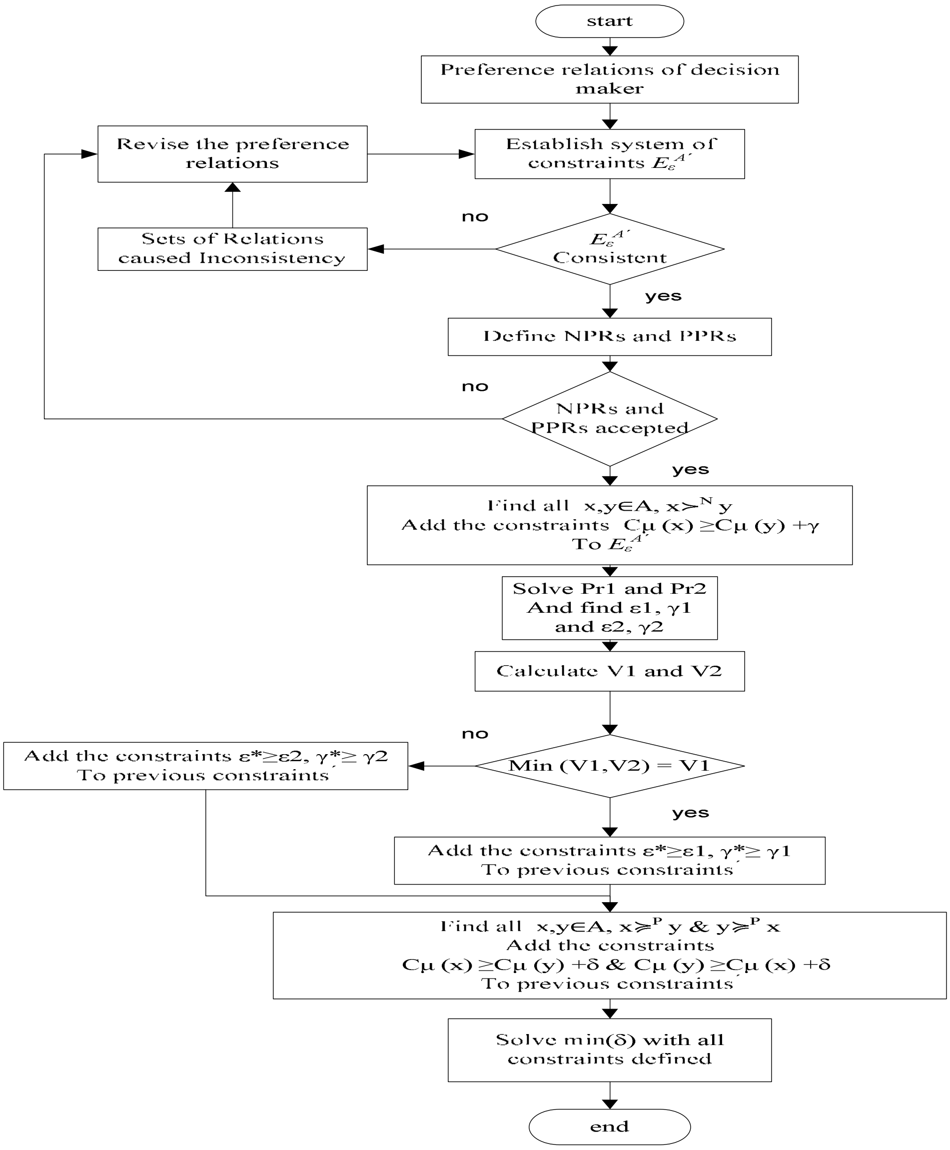

Figure 2. The flowchart of capacity definition model

Table 1. Factors, Factors importance and Partial scores

Group	Code	factor importance	Factor Title	Projects						
				P1	P2	P3	P4	P5	P6	P7
G1	HF1	10	control of HSE by owner	2	6	7	6	3	5	5
G2	HF2	8	government agencies' discipline in project site	2	6	6	6	5	5	6
	HF3	8	Government agencies interference in resource selection	8	6	6	6	8	6	6
	HF4	8	Intriguing between stakeholders	5	5	5	4	4	5	4
	HF5	8	The Non-governmental organizations (NGO's) safety orientation	1	3	6	3	7	3	8
	HF6	7	The tendency to local clothing	3	10	10	8	5	10	9
	HF7	7	Learning capabilities	10	7	5	4	4	7	6
	HF8	6	The drug abuse in project site	10	5	3	1	3	5	4
	HF9	3	The industrialization in the area	2	3	5	3	2	3	2
G3	HF10	6	MAPNA's HSE requirements and goals	9	7	7	4	3	2	2
G4	HF11	8	Contractors' experience and capabilities	5	3	2	1	1	3	2
	HF12	7	safety of material packing	8	4	5	5	8	9	9
	HF13	7	disturbance in works sequence	7	7	4	2	3	4	4
	HF14	6	Project's physical scope	9	7	2	3	4	6	3
	HF15	5	Contractors' collusion with owner or local people	5	3	3	4	3	3	5
	HF16	5	The waste released by rework	1	4	3	1	3	5	3
G5	HF17	8	Climate conditions	4.1	4	4	3.3	3.6	4	3.9
	HF18	6	suitability of transportation infrastructures	2	5	7	4	3	5	3
	HF19	5	camp's distance from project site	5	3	2	3	3	4	5
	HF20	4	The security of the site considering wild animals' threat (i.e., Snake, scorpion, etc.)	3	2	4	3	2	2	5

Table 1. Continue

Group	Code	factor importance	Factor Title	Projects						
				P1	P2	P3	P4	P5	P6	P7
G6	HF21	7	Project's complexity	5	5	3	3	5	5	3
	HF22	5	Project type	6	6	5	5	5	5	4
	HF23	4	Nearby industries' pollution	3	3	4	4	4	4	3

2. The factors interactions have been defined according to table 2. The coordinates indicate the indices of factors according to table 1. The interaction between factors of same group is shown by bold font. All interactions are negative in this case.
3. In order to build the pair-wise comparisons on importance of factors, the DMs are asked to define the importance of each factor in the interval [0-10] which have translated to [0,1] while running the algorithm. Then, the factors inside each subgroup are sorted according to their importance in table 1. This information is used in step 5.

Table 2. The factors interaction

	G1	G2	G3	G4
G1		(1,2) ,(1,3)	(1,10)	(1,11) ,(1,12), (1,15)
G2		**(2,3), (2,4), (2,9),(3,4), (3,6), (3,9), (5,9)**		(2,11), (2,12), (3,15), (3,16), (4,15)
G3			--	(9,13)
G4				**(11,12), (11,13), (11,15), (11,16), (13,16), (15,16)**

4. Then, terminated power plant projects of MAPNA MD-2, including seven projects, have been selected for evaluation. These projects are shown with P1,…,P7.
5. The external factors score have been defined in two levels. At first level, the scores of factors of each sub-group are aggregated. If there is any interaction between factors of the same sub-group (G2 and G4 groups), the sub-group's aggregated score are defined by CI using

proposed algorithm. In this case pair-wise comparisons on importance of factors are made considering the order of factors in its subgroup in table 1. The CI's coefficients for aggregating the scores of sub-groups G2 and G4 are shown in tables 3 and 4, and the aggregated scores in table 5. Otherwise, the scores can be aggregated by weighted arithmetic mean considering the weights shown in third column of table 1 (sub-groups G1, G3, G5 and G6). Finally, all sub-groups scores should be aggregated to define the final score of external factors affecting HSE of each project (the plot shown by HF in figure 3). In order to define the system of coefficient for running algorithm at this step, the following comparisons have been made: (1) the pair-wise comparisons of importance and intensity of importance of sub groups by analyzing their mean weight according to table 1, (2) interactions between factors of sub groups, (3) intensity of interaction between subgroups by considering the ratio of existing interactions to potential interactions. The final score of each project on both factors and output results are shown in figure 3.

Table 3. The Choquet Integral's coefficients for group G2

	HF2	HF3	HF4	HF5	HF6	HF7	HF8	HF9	Factors importance
HF2		-0.01	-0.01	0.00	0.00	0.00	0.00	-0.01	0.57
HF3			-0.01	0.00	-0.01	0.00	0.00	-0.01	0.08
HF4				0.01	0.00	0.00	0.10	0.00	0.08
HF5					-0.12	-0.01	0.00	-0.01	0.07
HF6						0.00	0.00	0.00	0.06
HF7							0.00	-0.05	0.05
HF8								0.00	0.05
HF9									0.03

Table 4. The Choquet Integral's coefficients for group G4

	HF11	HF12	HF13	HF14	HF15	HF16	Factors importance index
HF11		-0.038	-0.038	0.000	-0.038	-0.038	0.263
HF12			0.006	0.000	-0.141	0.026	0.224
HF13				0.000	0.000	-0.038	0.186
HF14					0.000	0.000	0.147
HF15						-0.038	0.109
HF16							0.071

Table 5. The aggregated scores of subgroups affecting HSE

	projects						
Subgroups	**P1**	**P2**	**P3**	**P4**	**P5**	**P6**	**P7**
G1	2	6	7	6	3	5	5
G2	**3.72**	**6.427**	**6.11**	**5.533**	**5.272**	**5.85**	**6.166**
G3	9	7	7	4	3	2	2
G4	**6.837**	**4.881**	**3.49**	**2.945**	**4.266**	**5.702**	**4.984**
G5	3.55	3.7	4.3	3.4	3	3.9	4.1
G6	4.813	4.8	3.9	3.9	4.8	4.8	3.313

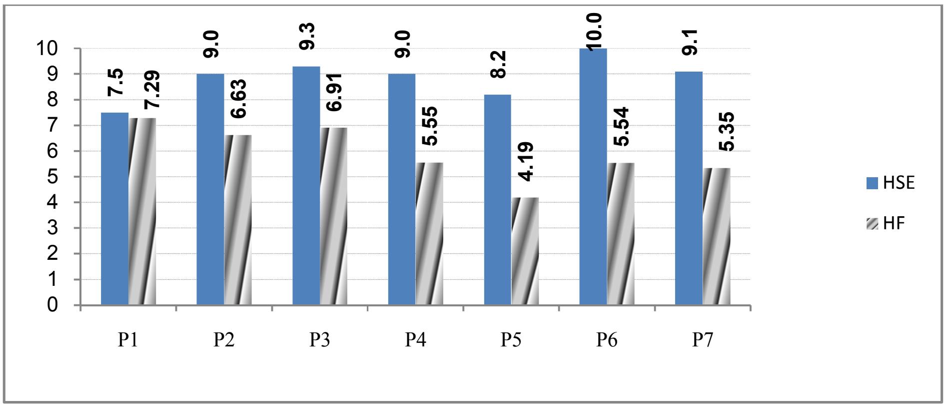

Figure 3. The factors aggregated scores (shown by HF) and the output result of HSE (shown by HSE)

To sum up, modified algorithm has been used three times for aggregation. Twice for aggregating the factors of second and forth subgroups namely *social, political and economic factors* (G2), and *contractors* (G4) to define these subgroups impact on HSE and once when aggregating all six subgroups scores to define the final score of external factors. At each step, two LP's have been solved; Pr1, which is exactly the same as primary algorithm, and Pr2, which is defined in modified algorithm. As it is shown in Table 6, Pr2 led to less variance than Pr1 in all third runs of algorithm ($V^*=V_2$, $\varepsilon^*=\varepsilon_2$ and $\Upsilon^*=\Upsilon_2$ in all cases). Thus, the constraints to be added in step 11 are $\varepsilon\geq\varepsilon_2$ and $\Upsilon\geq\Upsilon_2$. In all three cases, adding the constraints related to PPR at step 12 and calculating min δ at step 13 didn't lead to feasible solutions, so the best solutions calculated so far, *i.e.* Pr2 solutions, define the final capacity in all three cases. Consequently V1 and V2 are the variance of primary algorithm and the algorithm proposed in this paper. As it has mentioned V2 is less than V1 in all cases and modified algorithm leads to more even solutions compared to primary algorithm.

Table 6. ε, ϒ and variance of Pr1 and Pr2 in algorithm runs.

	problems	ε	ϒ	V
G2	Pr1	0	0.063	0.038
	Pr2	**0.007**	**0.058**	**0.03**
G4	Pr1	0	0.092	0.032
	Pr2	**0.038**	**0.072**	**0.017**
HSE factors	Pr1	0	0.2	0.034
	Pr2	**0.1**	**0.107**	**0.026**

As it was expectable, the output results of projects HSE performance don't follow the same scheme as external factors affecting HSE. *I.e.*, there is a gap between them. The gap is deep in some projects and shallower in some other. It is ignorable in project 1 and gets deeper in projects 4, 5, 6 and 7. Actually output result of each project depends on two main issues: the external factors affecting HSE and the inter-organizational factors. It can be concluded that in project 1 the output result is in accordance with external factors impact, it means that the internal factors didn't make any especial effort to enhance the output results. Maybe there was no need for additional effort because the external factors' final score was itself in satisfactory level. But in projects 4, 5, 6, and 7 the environment gets worse especially in project 5, nevertheless the output results are much more satisfactory than projects 1 and 2 in which the environmental factors were in better conditions. So it can be inferred that internal factors did make a significant effort to compensate the external factors' effect.

6. Conclusion

This paper utilized the CI to evaluate the effect of external factors on the HSE performance of MAPNA MD-2 projects. A modification to most representative capacity definition method is proposed to define the coefficients of CI. This method modified the primary method by improving the entropy of capacity and consequently the reliability of capacity in evaluating the projects which are not considered in decision maker's comparisons. The results show that modification improves the entropy of capacity by reducing its variance. So the aggregation functions defined at each step, either linear, *i.e.* WAM, or nonlinear, *i.e.*, CI, constitutes the comprehensive evaluation model for measuring the impact of external factors on HSE performance of upcoming projects of MD-2. The external factors aggregated score defined by CI are compared with output results of HSE. Some projects output results were much satisfactory than external factors affecting them, as the projects output result is dependent upon external and internal factors, it can be concluded that in these cases the internal factors including project managers and team member were making a considerable effort to compensate the deficiency of external factors.

The proposed method can be used for evaluation purposes in all industries. It also can be used for evaluating a specific project's performance improvement by measuring its performance at its different milestones and taking strategies based on performance analyses.

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