QUALITATIVE KNOWLEDGE ACQUISITION AND REPRESENTATION FOR CONSTRUCTION PERFORMANCE DIAGNOSIS

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ABSTRACT

Construction performance modeling is an integral part of managing risk on construction projects. Traditionally, estimating cost, schedule and productivity are carried out assuming the uncertainty involved in these elements is purely probabilistic. However, in most real-life problem scenarios, uncertainties encountered can not be described exclusively by statistical means. There are many factors that affect construction performance, which cause uncertainty due to vagueness rather than randomness. The theory of fuzzy sets provides a mathematical technique to capture and model uncertainty caused by vagueness using membership functions. However, knowledge acquisition from construction experts, in a systematic manner, remains one of the challenges of using fuzzy set theory in an effective manner. This paper presents a systematic methodology to elicit and represent qualitative construction performance knowledge from a group of experts. The novelty of this approach lies in the way how subjective estimates are represented. Use is made of an example project to illustrate the modeling concepts presented.

KEY WORDS

Construction performance, linguistic variables, knowledge acquisition, semantic differential.

INTRODUCTION

Construction performance modeling is an integral part of managing risk on construction projects. Traditionally, estimating cost, schedule and productivity are carried out assuming the uncertainty involved in these elements is purely probabilistic, for example, using traditional techniques such as range estimating and stochastic scheduling. However, in most real-life problem scenarios, uncertainties encountered can not be described exclusively by statistical means. There are many factors that affect construction performance, such as weather conditions, crew skill and experience, ground conditions, and site congestion, all of which cause uncertainty due to vagueness rather than randomness. The construction management team's knowledge about the context and factors that affect performance is

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mainly available in qualitative form rather than quantitative or mathematical terms. Both the parameters affecting performance (e.g., cold temperature, average skill, poor ground conditions) and their relationships (e.g., cold temperature and over-manning have a strong influence on labour productivity) can be more easily defined in linguistic terms rather than mathematical means. Thus modeling construction performance can benefit from a technique that has the ability to compute with words. The theory of fuzzy sets (Zadeh 1965; Zadeh 1975) provides a mathematical technique to capture and reason with linguistic variables (words) using membership functions.

Knowledge acquisition from construction experts, in a systematic manner, remains one of the challenges of using fuzzy set theory effectivly. This paper presents a systematic methodology to elicit and represent qualitative construction performance knowledge from a group of construction experts.

CONSTRUCTION PERFORMANCE DIAGNOSIS

Construction performance diagnosis involves identifying causes of performance deviations. To ensure efficient performance of a diagnostic reasoning system, the acquisition and representation of knowledge from domain experts becomes the most essential task in the development process. Construction projects are managed by a group of experts, ranging from frontline supervisor, representing each trade, to the construction manager who oversees the entire project operations. The first step towards identifying causes of performance deviations is to assess the working conditions on a daily basis. The study presented in this paper is designed to collect data to reason about construction productivity at the activity-level (and summarizing upwards). Thus knowledge acquisition is carried out at the front-line supervision level. A structured approach is required to obtain subjective assessments (i.e., fuzzy linguistic estimates) of daily working conditions from multiple experts. Furthermore, this approach should facilitate the aggregation of subjective assessments across multiple experts and across different time intervals as well.

Generally, in most studies, a unipolar scale (e.g., 0 to 10, zero being the lowest and 10 being the highest) is selected to represent an individual's subjective judgment. This paper presents a measurement technique that is based on bipolar scales, named as the semantic differential technique for structuring subjective assessments of construction performance variables. The rationale in selecting a bipolar scale, instead of a traditional unipoar scale is presented in the next section.

SEMANTIC DIFFERENTIAL ANALYSIS

The method of Semantic Differential (Osgood et al. 1957) offers a simple, reliable and widely used method to measure the connotative meaning of objects, events and concepts. It is a type of rating scale defined using bipolar adjectives (e.g., cold-warm, light-heavy, etc.). The adjectives are usually scaled in 7 steps, represented by seven linguistic hedges, as shown in Figure1.

(concept)

polar term **X**	☐	☐	☐	☐	☐	☐	☐	polar term **Y**
	1	2	3	4	5	6	7	

1. extremely X
2. quite X
3. slightly X
4. neither X nor Y; equally X and Y
5. slightly Y
6. quite Y
7. extremely Y

Figure 1. Bipolar scale.

The subject's placement of the concept on the adjectival scale indicates the connotative meaning of the concept. Studies carried out by Osgood et.al. (1957) on a large number of different subjects in many different experiments, found that "with seven alternatives all of them tend to be used and with roughly, if not exactly, equal frequencies. When nine alternatives were used, where "quite" is broken into "considerably" and "somewhat" on both sides of the neutral position, it was found that all three discriminative positions on each side had much lower frequencies". This finding is consistent with Saaty's (Saaty 1980.)seven point scale. To each of the seven positions on the bipolar scales, a digit is assigned arbitrarily. These digits may be either 1,2,3,4,5,6,7 or -3,-2,-1,0,1,2,3. For mathematical descriptions (described later), the choice makes no difference. In a 1 to 7 scale, as shown in Figure 1, "4" corresponds to the neutral point, in -3 to +3 scale, 0 represents the neutral point.

The choice of bipolar scales to represent the experts' evaluation (i.e., fuzzy linguistic estimates) has several advantages:

1. **Intensity and Direction:** Bioplar scales represent intensity as well as the direction of the fuzzy estimate while a traditional unipolar only provides the intensity.
2. **Multidimensionality**: If we use a unipolar scale, we presume that the factor in question can be represented unidimentional. In other words, the best reason to use unidimensional scaling is because we believe the concept we are measuring really is unidimensional in reality. Factors such as site congestion, for example, can be represented by both manpower density and equipment mobility. In such situations, we can use bipolar scales to capture the multidimentionality of such factors.
3. **Planned conditions**: In some cases, the neutral values of the bipolar scale (i.e., number 4) represent the planned conditions of the causal factors (e.g., temperature, wind), which can be used to identify implicit planned working conditions. This information can be useful in conducting variance analysis using fuzzy linguistic estimates.

DAILY WORKING CONDITION ASSESSMENT

This section describes an approach that provides a well-defined methodology for construction managers to assess daily working conditions using fuzzy linguistic estimates based on semantic differentials.

Figure 2 shows a sample daily working condition report. “Steel erection” is selected as the activity, *R,* for illustration.

Activity: STEEL ERECTION

GF/Foreman: **Date:**

DAILY WORKING CONDITION REPORT

			Extremely	Quite	Slightly	Both/ N.A	Slightly	Quite	Extremely	
* Today's Crew Productivity		Low	1	2	3	4	5	6	7	High
1. Crew size (no. of workers/crew)	(_ _ _)	Small	1	2	3	4	5	6	7	Large
2. Absenteeism (no. of crew members absent)	(_ _ _)	Low	1	2	3	4	5	6	7	High
3. Rework (Rework hours)	(_ _ _)	Low	1	2	3	4	5	6	7	High
4. Temperature		Cold	1	2	3	4	5	6	7	Warm
5. Total precipitation		Low	1	2	3	4	5	6	7	High
6. Wind speed		Low	1	2	3	4	5	6	7	High
7. Equipment availability (no. of cranes available)	(_ _ _)	Poor	1	2	3	4	5	6	7	Good
8. Equipment suitability		Improper	1	2	3	4	5	6	7	Ideal
9. Tools condition		Poor	1	2	3	4	5	6	7	Good
10. Consumables availability		Poor	1	2	3	4	5	6	7	Good
11. Material availability		Poor	1	2	3	4	5	6	7	Good
12. Congestion on work location		Low	1	2	3	4	5	6	7	High
13. Access to work location		Restricted	1	2	3	4	5	6	7	Unrestri -cted

<u>Example</u>

Crew Size (Average 10, Today 9)
(No. of crew members)

Small 1 2 3 4 5 6 7 Large

1. *extremely* Small
2. *quite* Small
3. *slightly* Small
4 *Neither* Small nor High; *equally* Small and Large
5. *slightly* Large
6. *quite* Large
7. *extremely* Large

Figure 2. Sample working condition report.

This working condition report, C_R, represents the multidimensional space of the concept: daily working condition for steel erection. The list of causal factors (L_k, k=1 to m, where m is the total number of causal factors in C_R) represent the dimensions of the semantic space. Each dimension (i.e., each causal factor) is represented using a bipolar scale assumed to represent a straight line function that passes through the origin of the space. A sample of such scales then represents a multidimensional space. Raw data obtained from "daily working condition report" are a collection of check marks against bipolar scales, S_p^k, where $p \in \{1,2,3,4,5,6,7\}$. As shown in Figure 2, the scale values are labeled using seven linguistic hedges to help experts make adequate distinctions amongst them.

Assume that n frontline supervisors that represent C_R reported their fuzzy linguistic estimates on L_k (k= 1 to m, where m is total number of causal factors) on day t. This results in a set of pairs $\langle x_{L_k}, S_{i,p}^k \rangle$, where x_{L_K} represents the corresponding objective measure of the causal factor L_k on the period concerned (e.g., daily). $S_{i,p}^k$ represent the fuzzy linguistic estimate provided by expert i on variable L_k, ($p \in \{1,2,3,4,5,6,7\}$, fuzzy linguistic estimate).

As illustrated in Figure 3, for a given activity on a certain day, the working condition report C_R provides $n*m$ matrix of data points. An alternative representation of the n*m matrix is shown in figure 4.

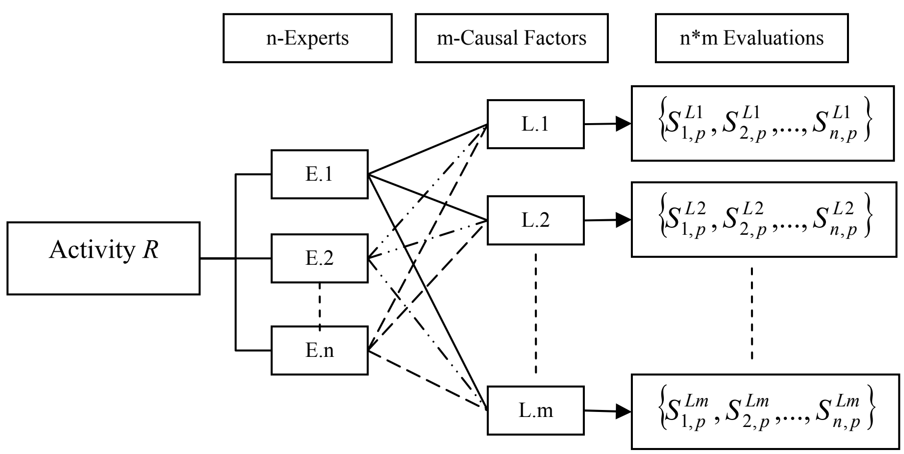

Figure 3. Multiple fuzzy linguistic estimates from daily working condition report

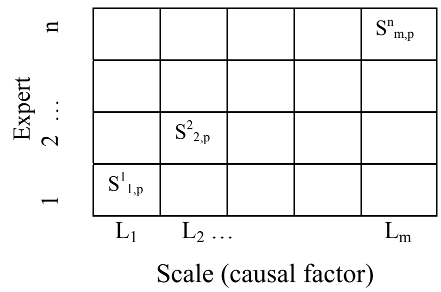

Figure 4. Matrix representation of multiple fuzzy linguistic estimates

When the fuzzy linguistic estimates are obtained over a period of time, T, the resulting matrix of data (n*m*T) can be represented as shown in Figure 5. Each cell in this matrix of data represents the judgment of a particular causal factor by a particular expert on day *t*; each of the *n* slices represents the complete judgment of a single expert (i.e., one daily working condition report. Each of the m slices represents the assessment of a particular causal factor over the duration T.

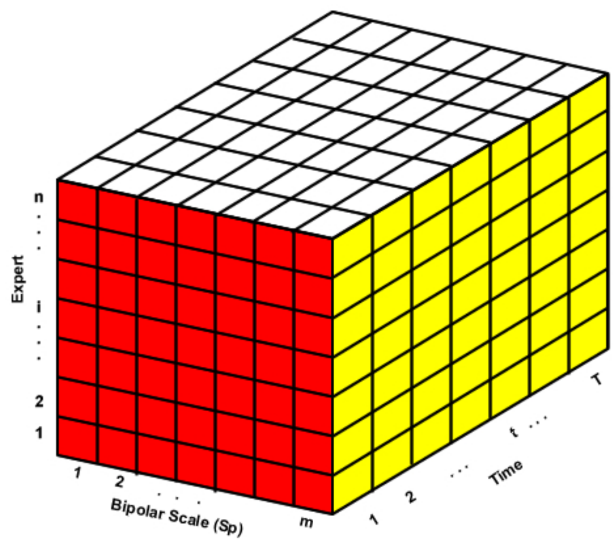

Figure 5. Rectangular solid of data representing experts' assesment over a period of T.

Aggregation of Data

There are three possible scenarios that may need aggregation of fuzzy linguistic estimates.

1. Mean response of group of experts: This is a case where the group estimate is required. Assume that we have *n* number of experts providing fuzzy linguistic estimates on causal factor L_k.

Let $S_p^k = \frac{1}{n}\sum_{i=1}^{n} S_{ip}^k$ (1)

S_p^k represents the mean response of the group of experts. It may be viewed as a probabilistic interpretation of the (mean) bipolar score. Equation 1 can be generalized by allowing one to distinguish degrees of competence, c_i, of the individual experts (Klir and Yuan 1995). This results in the formula

$$S_p^k = \sum_{i=1}^{n} c_i \cdot S_{ip}^k \quad (2)$$

2. Weekly (or monthly) averages: This is a case where data need to be aggregated across time (e.g., in the case where weekly averages are obtained from daily values). In this case;

$$S_p^k = \frac{1}{T}\sum_{i=1}^{T} S_p^k \quad (3)$$

where T is total number of days across the time period concerned.

3. Composite causal factor score: In cases where multi-level representations are required and composite factors are identified, to obtain composite causal factor scores, the (root) causal factor scores are summed and average over the scales. The composite causal factor score is

$$S_p^{\hat{k}} = \frac{1}{q}\sum_{i=1}^{q} S_p^k \quad (4)$$

Above equations provide a strategy to aggregate linguistic assessments when necessary.

FIELD STUDY

A field study was designed and conducted to test and validate the concepts presented above. This field study is carried out at a pipe module fabrication facility of a leading industrial contractor, located in Edmonton, Alberta. A total number of fifteen front line supervisors representing 5 trades (ironworkers, pipefitters, equipment operators, electricians, and carpenters) and 9 different activities (i.e., steel erection, pipe fitting and installation, welding, hydrotesting, glycol tracing, material handling, equipment operation, carpentry/scaffolding, and electrical) completed the study over a sixty workday period (during the summer of 2005. The experience of the group of experts (frontline supervisors, otherwise known as foremen) ranged from 6 to 32 years in the trade, averaging 20 years.

ANALYSIS OF FUZZY LINGUISTIC ESTIMATES

To determine the effectiveness of the proposed semantic differential scales to obtain fuzzy linguistic estimates, an analysis was carried out on selected causal factors. Results related to the causal factor "temperature" are discussed in this section. Figure 6 shows how daytime average temperature varied over the period of study. Temperature values were collected at the site by setting up a professional wireless mini-weather station (Model: WS-2315AL by La Crosse Technology).

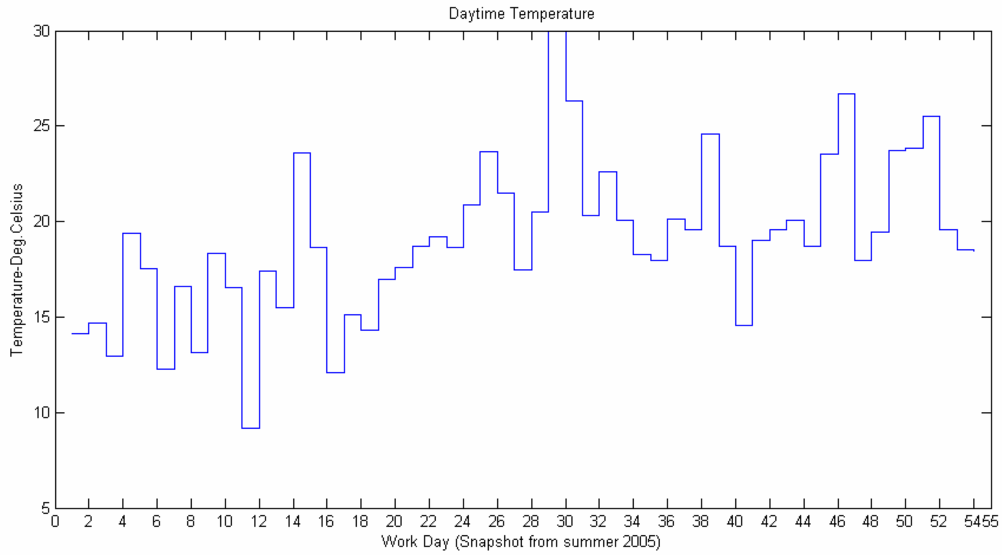

Figure 6. Day time average temperature (degrees Celsius)

Figure 7 shows the average fuzzy estimates aggregate from all experts (assuming equal competency levels) against the daytime average temperature. Note that multiple dots for the same x-axis values (i.e., degrees Celsius) indicate that the same daytime average temperature was recorded on multiple days during the period studied.

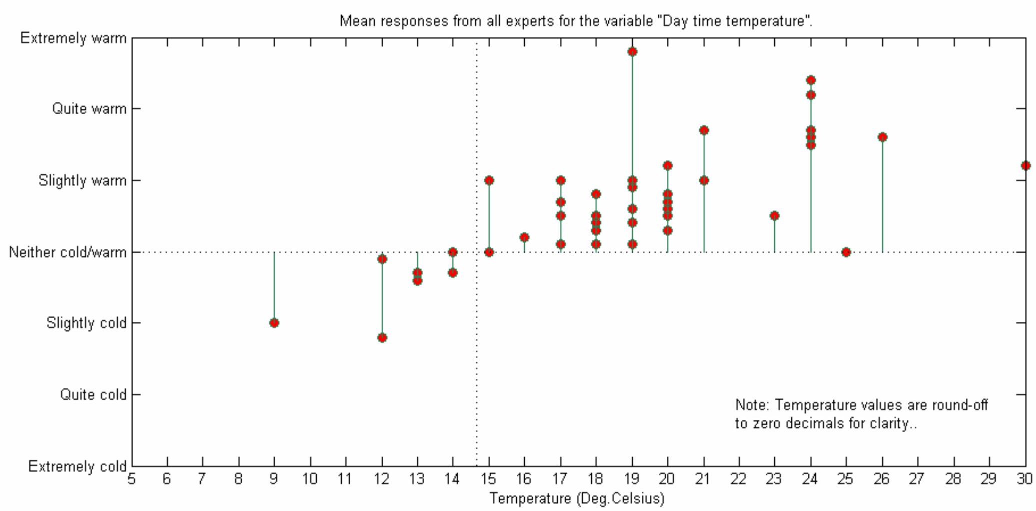

Figure 7. Mean estimated values for temperature

Multiple dots for the same temperature value also indicate that different expert evaluations were obtained for the same value of temperature (on different days of the month/season). However, as shown in Figure 6, in most cases the variation of the fuzzy estimates is low and remained in between two linguistic values. For example, the value of 18 degrees Celsius is recorded 5 times during the study period. The mean value of fuzzy linguistic estimates for all five days remained in between "neither cold/warm" and "slightly warm". Similar results were observed for the temperature values 12, 13, 14, 15, 17, 21, and 24. This indicates that, for the period studied (i.e., summer 2005), the mean estimates (of the group) are nearly consistent.

A sample activity level analysis (for structural steel erection) for the same causal factor (i.e., temperature) is shown in Figure 7. The subjectiveness of individual assessments is clearly visible in the Figure 7. Nonetheless, the assessments are still in between two linguistic values in 85 percent (18 out of 25) of the cases.

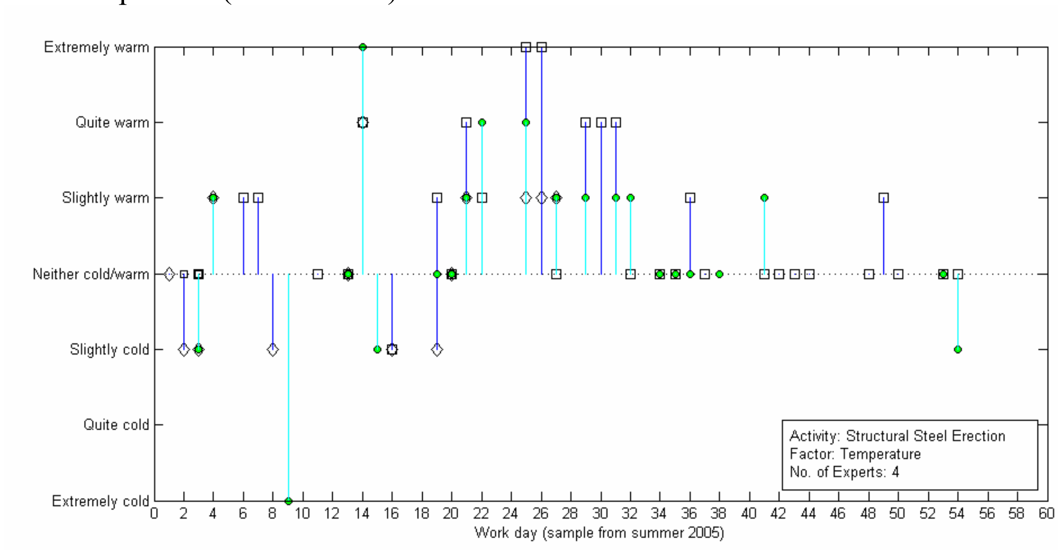

Figure 8. Individual estimated values for temperature by Steel erection experts

A similar type of analysis was carried out for twenty causal factors across four different activities. The consistency of the experts' linguistic assessments was above 72 percent in all of the cases, which indicates that the proposed methodology is a practical tool for acquiring and representing subjective assessments from a group of individuals for construction performance diagnosis.

These fuzzy linguistic assessments can be directly used for a number of purposes, for example (1) to identify and evaluate implicit planned working conditions, and (2) to identify the causal factors that vary considerably. Additionally, these linguistic assessments can be transformed into sample membership values so that can be used as input to fuzzy logic based systems.

SUMMARY

In this paper, a structured approach to elicit and represent construction experts' assessments on daily working conditions using semantic differential measurements is proposed. Algorithms are proposed to aggregate linguistic assessment to represent information at different levels, such as group estimates and weekly average values. Currently research is underway to construct fuzzy membership functions using sample membership values obtained using semantic differential approach proposed in this paper to develop construction performance diagnostic reasoning systems.

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NOTATION

The following symbols are used in this paper;

C_R	=	working condition report of Activity *R*.
i	=	expert;
L_k	=	causal factor
m	=	total number of causal factors
n	=	total number of experts
$p \in \{1,2,3,4,5,6,7\}$	=	values that represent the linguistic hedges of bipolar scale *S*.
q	=	total number of sub causal factors consists in the composite factor
R	=	activity
S	=	bipolar scale
$S^{k}_{i,p}$	=	linguistic assessment of causal factor L_k by expert *i*
$S^{\hat{k}}_{p}$	=	composite causal factor score
x_{L_K}	=	objective measurement of causal factor L_k