ISSUES AND CHALLENGES OF CONSTRUCTION PERFORMANCE DIAGNOSTIC MODELING

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ABSTRACT

A decision support system that makes it possible to diagnose root causes of performance deviations, in a timely manner, would be an attractive way to improve project performance and meet or exceed project performance goals. The diagnostic context investigated in this paper is construction performance reasoning. Performance diagnosis intends to isolate the cause(s) of a performance deviation by collecting and analyzing information on performance indicators using field measurements, subjective judgments, and other information sources (e.g., time-cards, weather data, etc.). Due to the complex interrelationships between performance variables, the diagnosis of construction performance has become a complicated undertaking.

Since a number of different approaches to diagnosis have been explored over the years by other industries, it is useful to establish the appropriate circumstances for their use, and specifically identify suitable approaches for construction performance diagnosis. This paper reviews a range of diagnostic approaches to identify a suitable model/s that can actually be applied to the construction management domain for performance reasoning. The relative advantages and disadvantages of these models are highlighted.

This paper also identifies the issues and challenges that need to be addressed in terms of developing a robust diagnostic model for reasoning about construction performance. Key issues are categorized into four different aspects (1) data and information related issues, (2) knowledge acquisition and representational issues, (3) input-output mapping issues, and (4) reasoning issues. This paper concludes with a summary providing a match between issues identified and techniques that possibly can be used to solve the issues, to develop a robust diagnostic model for reasoning about construction performance.

KEY WORDS

Diagnosis, construction, performance, modeling, computational intelligence.

INTRODUCTION

A decision support system that makes it possible to diagnose root causes of performance deviations, in a timely manner, would be an attractive way to improve project performance and meet or exceed project performance goals. The diagnostic context investigated in this paper is construction performance reasoning. Performance deviations are detected when one or more key performance indicators(KPI) (e.g., labour productivity factor, cost variance, rework index) go outside a given range or change significantly from their planned values. Performance diagnosis aims to isolates the

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cause(s) of a performance deviation, by collecting and analyzing information on performance indicators using field measurements, subjective judgments, and other information sources (e.g., time-cards, weather data etc.). Often, diagnosis is performed by a construction manager, and it is an important function of construction project control. A decision support system that makes it possible to diagnose root causes of performance deviations, in a timely manner, would be an attractive way to improve project performance and meet or exceed project performance goals.

A sample construction performance diagnostic problem scenario is given below:

"Yesterday's Labour productivity performance (measured as earned vs. actual man-hours) of structural steel erection is low (e.g. 0.65)." Why?

Identifying relevent causes to such a performance deviation, in a timely manner, is a key task of construction project control. However, due to the complex dynamic nature of construction projects, the diagnosis of construction performance has become a complicated undertaking. Maloney (1990) reported that it is crucial to respond promptly to evidence of poor performance and take corrective actions to eliminate its causes. According to Maloney (1990), there are two key factors that hinder construction managers (CM) from taking actions in a timely manner: (1) The CM's extremely demanding schedule of routine work, and (2) the short duration of activities and/or construction projects. Maloney proposed a performance analysis framework that guides an individual through a flowchart, which analyzes causes of unacceptable performance. Although it has been identified that speedy response to evidence of poor performance is required, Maloney's framework does not provide a quick response. Instead, it requires an individual to go through the entire process, repetitively, and it also does not facilitate identifying the root causes of the problem. In a comprehensive review of construction performance models, Li et al. (2005) identified that there is no "definitive model for either predicting or explaining performance; most of the models described are more research than practice oriented; and, strong consensus as to the most important factors to use, what their definition should be, how best to express outcomes for them, or what the relationship amongst factors is, if any".

A number of different approaches to diagnosis have been explored over the years by other research communities, mainly in the chemical and power industries (e.g., Corea et al. 1992; Sugeno and Yasukawa 1993), where definitive process models comprised of physical and readily measurable variables exist. It is useful to establish the appropriate circumstances for their use, and specifically identify suitable approach for construction performance diagnosis. Rest of this paper is organized into three sections. The following section reviews a range of diagnosis techniques to identify a suitable model/s that can actually be applied to the construction management domain for performance diagnostic reasoning. It will be followed by a discussion on key issues and challenges of construction performance modeling. A summary providing a match between issues identified and techniques that can be used to solve the issues, to develop a robust diagnostic model for reasoning about construction performance, concludes the paper.

DIAGNOSIS TECHNIQUES: A REVIEW

Over the last two decades, diagnosis has been an active area of research, where a larger part of the work has been concerned with the diagnosis of man-made artifacts such as electronic devices or with medical diagnosis. A comprehensive review of literature suggests that different diagnosis techniques can be categorized into four; (1) control theory approach, (2) Artificial Intelligence approach, (3) Computational intelligence approach, and (4) hybrid approach. Figure 1 graphically illustrates the taxonomy of these diagnostic techniques.

In control theory, the diagnostic model is numerical, generally represented as a set of differential algebraic equations. The anomaly detection and cause identification is performed using a specification of the different failure modes (problem scenarios) of the system along with a description of how these problems are manifested within the behavior of the system (Clancy 1998). A strictly numerical representation of the construction performance problem is not possible due to the nature of the construction work in a dynamic, uncontrolled and labor intensive manner with numerous interacting qualitative and quantitative variables. Furthermore, due to the dynamic nature (i.e., changing state of the measurable parameters at every step of time) of performance factors, specifying all of the possible problem scenarios that may be encountered becomes impractical.

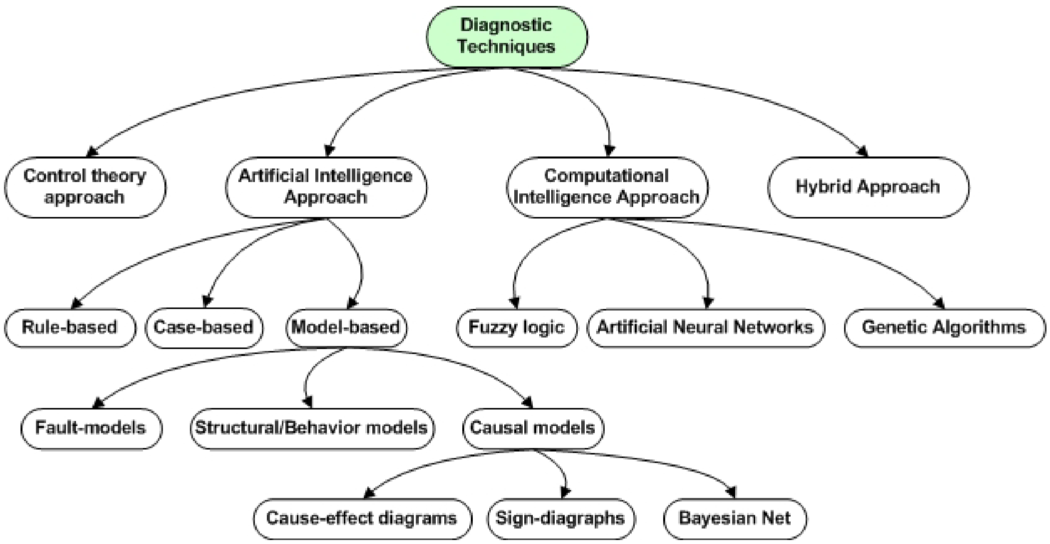

Figure 1. Taxonomy of different diagnostic techniques

In contrast, an artificial intelligence (AI) approach considers diagnosis as a reasoning process and tries to reproduce human reasoning (Gentil et al. 2004). Several AI diagnostic techniques are available, such as rule-based reasoning (e.g. (Chou et al. 1994)), case-based reasoning (e.g., Sharma and Sleeman 1993), and model-based reasoning (e.g. Clancy 1998).

In rule-based systems, the empirical information and experience is encoded in the form of rules which generally take the form "IF symptom(s) THEN diagnose(s)." Overall, rule-based diagnosis is only feasible for problems for which any and all knowledge in the problem area can be written in the form of if-then rules, and for which the problem area is not large. Depending on the problem, it may require hundreds, or even thousands of rules. If there are too many rules, the system can become difficult to maintain. Furthermore, the difficulty of acquiring the knowledge to build the rule-base, known as the knowledge acquisition bottleneck, is the main limitation of this approach.

Case-based reasoning (CBR) is a powerful approach when much experimental data describing faults/deviations are available. A case-based reasoner works by matching new problems to "cases" from a historical database and then adapting successful solutions from the past to current situations. The most challenging part of implementing a CBR model is the capturing of historical information to form the cases. In other words, CBR also suffers from the impact of the knowledge acquisition bottleneck. In construction, however, historical information related to construction performance indicators and related variables are available. If a systematic methodology to collect data in the form of input-output pairs is employed, the CBR approach can be a viable approach to assist construction performance modeling.

Model-based diagnosis, also referred to as consistency-based diagnosis (Reiter 1987) provides an alternative "implicit behavioral approach" to system modeling. They are appropriate when an abstraction of the quantitative modeling is sought in order to facilitate interaction with a human reasoner. Poole (1992) identifies two extremes of the model-based diagnostic problem: (1) consistency-based approach where normal-operation-oriented diagnosis is carried out based on the knowledge about how components are structured and work normally, (2) adductive approach, where abnormal-operation-oriented diagnosis is carried out using knowledge about how the components are affected by some specific faults.

Fault models (or fault dictionaries) anticipates the type of faults that may occur, and only model these. Model simulation provides a list of fault/symptom pairs, which produce the fault dictionary. According to Fenton (2001a) this method has primarily been applied to the diagnosis of digital circuits. In contrast, models based on structure and behaviour (e.g., (Davis 1984)) models a correct behaviour. "The structure representation lists all the components and interconnections within the modeled system. The behaviour representation describes the correct behaviour pattern for each component. Both representations are often created using logical formulae, such as first order predicate calculus" (Fenton et al. 2001b).

Causal modeling (e.g., Gentil et al. 2004) is another AI diagnostic approach that focuses on representing qualitative knowledge. As cited in (Rasmussen 1993), " diagnostic judgment implies the perception of a causal relation between a state, an action, and the ultimate effect, as related to the current objective". Causal reasoning is an important approach in the diagnostic task. Causal graph-based diagnosis is appropriate where it is usually difficult and costly to develop precise mathematical models. Cause-effect diagrams (Ishikawa 1985), influence graphs (e.g., Gentil et al. 2004) and Bayesian networks (e.g.,Kirsch 1993) are few categories of causal models that found applications in diagnosis. Moselhi et al. (2004) proposed a construction performance diagnostic method based on predefined causal models, however the use of causal model concept is limited to show the relationship between quantitative performance indicators.

Cause-effect diagrams, otherwise known as fishbone diagrams, are very useful in analyzing and describing cause and effect relations in a qualitative way. In a pilot study to identify and classify causes of construction field rework, Fayek et al. (2004) used cause-effect diagrams as the framework for diagnosing causes of field rework, with the assistance of field construction personnel's input. The required extent of manual user input and the subjective nature of assessments restrict the feasibility of this approach for daily performance diagnosis on large-scale projects.

Influence graphs are another type of causal approach to reasoning about the way in which normal or abnormal changes propagate. The graph nodes represent the system variables; the directed arcs symbolize the relations among variables. Relations can be quantitative or qualitative. The simplest influence graph is the signed diagraph (SGD) where relations are represented by signs: "+" or "-". Iri et al. (1980) used SGD as the basic data structure for diagnosis. According to Gentil et al.(2004), over the years, this approach has been considerably enhanced, for example, Yu and Lee(1991) symbolized the variables as fuzzy sets to incorporate the continuous nature of the variables.

In Bayesian networks, entities are defined probabilistically, using prior knowledge and statistical data, in acyclic graphs where nodes are random variables and relationships between them are represented by arcs. Even though the concepts (or variables) can be represented more easily than by using rules, the knowledge acquisition bottleneck is a primary shortcoming. McCabe et al (2001) used Bayesian networks to assess productivity of construction operations. However, in most of the real-life problem scenarios, uncertainties encountered cannot be described exclusively by statistical means.

Diagnostic systems based on Computational Intelligence (CI) tools such as fuzzy sets (Zadeh 1965), artificial neural networks (ANN) (Meireles et al. 2003), and genetic algorithms (GA) (Holland 1975) are emerging as more realistic approaches due to their unique characteristics. Fuzzy set theory based diagnostic systems provide a good alternative for reasoning under uncertainty (e.g., (Dexter 1995; Sauter et al. 1994)). These systems are becoming popular because they provide human-like and intuitive ways of representing and reasoning with incomplete and imprecise information. However, fuzzy logic based systems do not have the ability to learn from experience (previous cases). In contrast, diagnostic systems based on Artificial Neural Networks (e.g., (Maki and Loparo 1997; Sorsa et al. 1991)) exploit self-learning capabilities using historical data. Additionally, ANN based systems provide a mathematical tool for modeling dynamic nonlinear relationships. The primary shortcoming of ANN systems is that they need significant amount historical quantitative data for their training.

As described above, each individual technique has its own advantages and disadvantages. Hybrid solutions can significantly enhance the robustness of a diagnostic system by capitalizing on the advantages of combing supplementary techniques. For example, Breese et al. (1996) combined case-based reasoning and Bayesian networks for diagnosis and troubleshooting applications, while Ariton et al. (1999)used a fuzzy-neuro architecture for modular fault isolation in complex systems. Liu and Yan (1997) combined fuzzy logic, neural networks and case-based reasoning to develop a system for diagnosing symptoms in electronic systems.

The selection of the appropriate technique or a hybrid combination of several techniques depends primarily on the diagnostic problem at hand. Each problem domain has its distinctiveness in terms of availability of data, problem complexity, dynamic nature, and so on. Hence, the following section provides a detailed discussion on the issues and challenges of developing robust construction performance models, with the intention of assisting in the selection of an appropriate diagnostic technique(s) for explaining construction performance.

ISSUES AND CHALLENGES

This section describes a list of key issues that need to be addressed in order to develop robust construction performance diagnostic models. These issues are categorized into four different areas: (1) data and information related issues, (2) knowledge acquisition and representational issues, (3) modeling issues, and (4) reasoning issues. Key challenges are identified, and prerequisites and desired properties of a diagnostic model are identified. Table 1 provides a summary of the issues and their challenges. Each issue is detailed further in this section.

DATA AND INFORMATION-RELATED ISSUES

Establishing practical and economical data collection procedures have a significant impact on the successful implementation of a diagnostic model. A contractor should be able to collect (daily) data on the values of the variables at the individual project/activity level, either in quantitative or qualitative form. Current information management systems available to contractors are limited to storing quantitative information compared to qualitative information (e.g., the complexity of a task, the level of site congestion). This is mainly due to a lack (or absence) of systematic procedures to collect and process, and store qualitative data. However, both qualitative and categorical variables play a major role in construction performance. Hence, any robust diagnostic tool should be able to utilize both quantitative and qualitative information.

Achieving planned performance depends on establishing planned conditions of factors that affect performance. A formal procedure is required in order to derive planned values from different sources such as, the master schedule, manpower estimates, past project records, and industry standards (handbooks).

The vast majority of the information related to construction performance modeling is characterized by uncertainty. Identifying the nature of uncertainty is crucial in selecting appropriate methods to manage it effectively and even use it profitably. Two kinds of uncertainty are encountered in construction performance modeling, ambiguity and vagueness. Ambiguity can be caused by the presence of random variables or approximate estimates. Vagueness arises from "a lack of precision (whose boundaries are not sharply defined) or a lack of understanding of an event, a proposition, a value, or a system (Ayyub 1991)". Vagueness can result from (1) qualitative (instead quantitative) information, (2) incomplete or vague expert knowledge, and (3) subjectivity in the information obtained from an expert. As an example, the suitability of a particular crane to hoist a pipe spool can be assessed by a crane operator as "fairly good". A robust diagnostic system should be able to represent and manipulate vagueness and statistical uncertainties.

Table 1. Issues and Challenges of Construction Performance Diagnostic Models

Issues	**Challenges**	**Properties/Prerequisites of a Diagnostic Model**
Data and information related issues	Field data collection and reporting	Practical and economical data collection procedures to capture both quantitative and qualitative data.
	Establishing normal functional parameters (performance baselines)	A formal procedure needs to be established to derive planned values from different sources.
	Uncertainty in data	Ability to compute with incomplete, qualitative, and subjective data.
Knowledge acquisition and representational issues	Non-verifiability of critical causal factors	Ability to use expert (causal) knowledge
	Incompleteness in the relation between key performance indicators and related causes	Ability to determine the strength of causal factors using historical data
Modeling issues	Complex non-linear system	Non-linear modeling capability
	Capturing dynamics	Adaptability via learning from past data
	Model transparency	Explanation capability of the model
Reasoning issues	Identification of multiple root causes	Identifying the significance of each causal factor in cases where multiple factors contributed to the performance deviation.
	Identifying contributing vs, counteracting factors	Identifying whether a certain causal factor is contributing towards or counteracting performance.
	Different levels of abstraction	Reasoning at multiple levels of abstraction.

Additionally, it is noteworthy to highlight the fact that obtaining a dataset with reasonable accuracy is challenging in construction. Incomplete and imprecise data due to measurement uncertainties and approximation are common. Thus it is always preferable to have a less data-hungry approach for diagnostic modeling in construction.

KNOWLEDGE ACQUISITION AND REPRESENTATION ISSUES

Due to the absence of explicit mathematical relationships between performance factors, experts' (domain) knowledge has to be exploited to identify the possible causes of performance deviations in construction. In other words, experts' mental models (causal maps) of the problem scenarios have to be used as the first step in identifying possible causal relationships. Based on construction managers' expertise, a representation of the behavior of the performance indicator in causal terms is very effective in describing complex phenomena, such as construction labor productivity deviation. In addition, since the majority of variables are qualitative, subjective measurement of each variable in predefined time intervals (e.g., daily) is also required for effective diagnosis.

Complex relationships between performance factors frequently exceed the construction managers' ability to conceptually identify causal relationships amongst them. Normally, there can be more than a handful of factors that can cause a given observation of deviation (e.g., low productivity).

Judging the degree of relatedness (contribution) of each factor is always challenging, especially due to the dynamic nature of construction projects.

Hence, domain expert knowledge (from those who have had years of experience working in construction) has to be acquired and presented in a way that enables a system to utilize the knowledge for its reasoning tasks. Generally in construction, front line supervisors (i.e. foremen) have a comprehensive knowledge of activities they supervise; accordingly eliciting the knowledge from frontline supervisors to identify plausible causes of performance deviations related to the activities they supervise is a viable option. One expert or a number of experts can be utilized as the primary source of domain expertise. McGraw and Warbison-Briggs (1989) identified four primary problems with knowledge acquisition from a single expert: (1) difficulty in allocating adequate time by an "already-busy" individual; (2) problems caused by different biases of human experts; (3) limitation to a single line of reasoning; and (4) incomplete domain expertise (the available knowledge in many practical situations is often incomplete and imprecise). In contrast, even though multiple experts can create a synergy, the involvement of multiple experts increases the complexity of the knowledge acquisition process. This is mainly due to the difficulty of merging each individual expert's knowledge structures into one group knowledge structure. Therefore a systematic procedure is required to combine multiple experts knowledge to make the diagnostic process efficient.

MODELING ISSUES

Successful diagnostic modeling requires a close match between the diagnostic model and the true underlying problem scenario associated with the model. Generally in construction, obtaining a quality dataset that can be used for input-output mapping is limited; hence the diagnostic models should have the capability to model with limited amounts of data. Additionally, following key modeling issues need to be addressed as well. Identifying the underlying dynamics of construction performance is extremely challenging due to complex nonlinear behavior of the causal relationships among variables. As shown in Figure 2, most of the construction performance indicators and related factors display the characteristics of a nonlinear system. Thus modeling for construction performance requires a methodology that is capable of mapping these complex nonlinear systems. Note that in the Figure 2, the variation is calculated by taking the difference between daily value and average value.

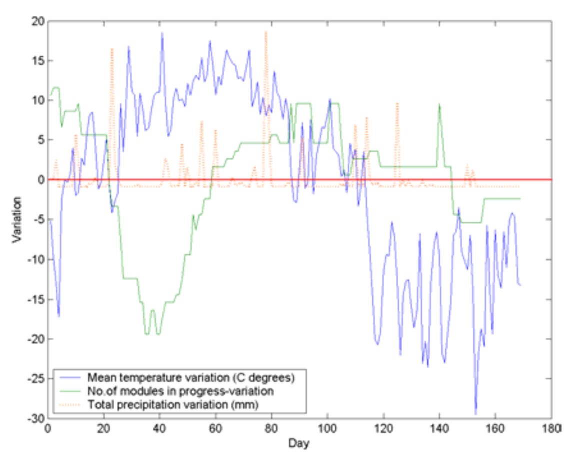

Figure.2. Example of non-linear behavior of performance variables (Temperature, Precipitation and number of modules in progress variation)

REASONING ISSUES

In addition to the above issues, construction performance diagnosis reasoning involves addressing a number of reasoning issues as follows:

1. Identification of multiple root causes: The most likely cause of a deviation can not be determined by looking at its immediate cause in isolation, since it generally depends on the relative strength of multiple of causes that occur simultaneously. Most construction performance diagnostic problems have multiple root causes; hence, identifying the significance (i.e., relative contribution) of each cause is important, so that corrective actions can be prioritized accordingly. Complex interrelationships between factors make it difficult to identify their individual impact on performance.
2. Identifying contributing vs. counteracting factors: Diagnostic models should have the ability to differentiate and identify contributing vs. counteracting factors during the course of inference. For example, low hydro-testing productivity may occur mainly because of {lack of supervision, high precipitation} despite {below average workload, average pipe-fitters availability, and no rework hours}. It is also noteworthy to highlight the fact that the same cause can act as contributing as well as counteracting cause, depending on the its activation status. For example, both low and high temperature variation can possibly impact labour productivity negatively, while average temperature can make the process efficient.
3. Issues related to different levels of abstraction: Another important issue of diagnostic modeling is the selection of an appropriate level of abstraction based on user requirements. Different stakeholders (e.g., client, construction managers, superintendents, and foremen) demand different perspectives (such as project level, work package, activity, and so on) on the same issue. Hence data must be clustered into multiple groups to represent the hierarchical structure of a problem scenario. One of the key challenges here is how to aggregate information (both objective and subjective). A robust diagnostic model, therefore, should not only possess capabilities to process subjective information, but also aggregate subjective data to provide meaningful representation at different levels of abstraction.

SUMMARY

All of above issues suggest that implementing a performance diagnostic reasoning system is non-trivial. In an attempt to deal with the above key diagnostic modeling issues, characteristic properties of different techniques discussed above are compared, as shown in Table 2.

Table 2. Key Modeling Issues and Possible Solutions

	Key Modeling Issues	**Possible Solution(s)**
1	Computing with incomplete, approximate and qualitative data	Fuzzy Set theory
2	Uuncertainty modeling casued by vagueness	Fuzzy Set theory
3	Expert knowledge representation	Rule based approach, Causal models
4	Non-linear and dynamic system modeling capability	Artificial Neural Networks (ANN)
5	Learning from previous data/ adaptive capability	Case-base reasoning approach (CBR) Artificial Neural Networks (ANN)
6	Identification of Multiple root cause and relative significance of each cause	Artificial Neural Networks (ANN)
7	Identifying contributing vs. counteracting causes	Fuzzy Sets (membership functions)

Based on the above summary, it can be concluded that a single technique does not solve all of the issues identified in construction performance diagnosis. Fuzzy set theory can be used to compute with incomplete, approximate and qualitative data, to manage uncertainty caused by vagueness, and identify contributing vs. counteracting causes. Causal models can be used to represent expert knowledge while, ANNs can be used to capture the nonlinearity and identify the significance of multiple root causes. Case-base reasoning approaches and ANNs can be used to learn from previous data.

Currently research are underway to develop a robust construction performance diagnostic model using fuzzy-neural networks that combines fuzzy sets (using fuzzy neurons), artificial neural networks, and case-base reasoning approaches.

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