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Learning Conceptual Design Rules: A Rough Sets Approach

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Abstract

The paper presents the results of a feasibility study conducted in the area of learning conceptual design rules governing the selection of wind bracing components in steel skeleton structures of tall buildings. The study's objectives were to compare decision rules produced by different learning systems using the same body of examples, and to formally verify these rules using the overall empirical error rate. The study was conducted using two learning systems, both based on the theory of rough sets: 1) System ROUGH which usually produces a large number of complex deterministic rules, 2) System DataLogic which can generate probabilistic rules, relatively simple and much fewer in number than in the case of ROUGH. All experiments were conducted using a collection of 374 examples of minimum weight (optimal) design of wind bracings in steel skeleton structures of tall buildings. The examples were prepared under identical design assumptions for a three bay skeleton structure of a tall building. They were produced using SODA, a computer software package for the analysis, design and optimization of steel structures. The paper gives a description of the learning experiments performed. It also provides a comparison of decision rules produced by DataLogic and Rough, and an analysis of empirical error rates obtained for the various collection of examples for ROUGH.

1 Introduction

Conceptual design of wind bracings in steel skeleton structures of tall buildings is usually understood as a process of selecting various structural components such as rigid frames, vertical or horizontal trusses, etc., which will be used together in a wind bracing in a given design case[2]. This process is still poorly understood, and there is little knowledge available, which could be used by a designer to make optimal decisions in conceptual design. The manual acquisition of conceptual design knowledge is in this case very difficult, if not impossible, because of the complexity of the structural problems involved and

Attribute Value	1	2	3	4	5
Number of Stories	6	12	18	24	30
Bay Length	20	30			
Wind Intensity	Low	High			
Static Character of Joints	Rigid	Hinge	Mixed		
Number of Bays Occupied by Bracing	1	2	3		
Number of Vertical Trusses	0	1	2	3	
Number of Horizontal Trusses	0	1	2	3	
Steel Unit Weight	Low	Medium	High		

Table 1: Knowledge Representation Space

secrecy surrounding details of the design of tall buildings. For these reasons, the automated knowledge acquisition, based on the use of machine learning and learning from examples of optimal minimum weight designs, is an attractive approach to acquiring design knowledge and to improve the present state of the art in the designing of wind bracings in tall buildings. Design knowledge is understood here as a system of relationships among various groups of attributes describing a given wind bracing. These relationships are decision rules which could be used to guide the designer in the conceptual design to make correct decisions regarding the configuration of a wind bracing.

In th paper, the results of a feasibility study are reported. The study was conducted using two learning systems, both based on the theory of rough sets, and its objective was to compare decision rules produced by both systems using the same body of examples, and to formally verify these rules using the overall empirical error rate.

2 Knowledge Representation

Knowledge representation used in the feasibility study contains three classes of nominal attributes and their values which describe wind bracings in the steel skeleton structures of the tall buildings[1]. The attributes were developed for the most common three-bay skeleton structures. The first class can be considered as a description of the building for which a given bracing is designed and is called "design requirements". The second class is a description of the wind bracing structural system. These two classes of attributes constitute together a collection of independent attributes. The third class of attributes contains in our case only one dependent attribute which is called "Unit Steel Weight". This attribute provides an evaluation of the unit steel weight of a given wind bracing for the design case considered. All attributes and their values are given in the Table 1.

The class of design requirements contains three attributes: 1. Number of stories, 2. Bay length, and 3. Wind intensity. The first two attributes are self-explanatory, while the third attribute identifies the location of the building with respect to the wind zones and it has two values for low and high wind intensity zones respectively.

The description of the wind bracing structural system is based on four attributes: 1. Static character of joints, 2. Number of bays occupied by bracing, 3. Number of vertical trusses, and 4. Number of horizontal trusses. The first attribute describes the joints in bracing in terms of their ability to carry bending moments and has such values as rigid, pinned, or mixed. The second attribute describes the width of bracing in terms of the number of bays entirely occupied by the bracing. The last two attributes identify the existence and number of vertical and horizontal trusses in the bracing respectively.

The dependent attribute "Unit Steel Weight", identifies the relative unit weight of the wind bracing structural system. For individual building heights unit weights are considered and normalized. The unit weights in three ranges [0, 0.33], [0.34, 0.66], and [0.67, 1] are considered low, medium, and high, respectively.

3 Knowledge Acquisition Tools

Two knowledge acquisition tools from REDUCT Systems, Inc. were used in the experiments described. Both tools are based on the theory of rough sets[3]. The tools are PC-based and they are aimed at analysis and modeling of inter-attribute relationships in attribute-value systems, which are also called information systems. The tools have been developed as a result of research on machine learning applications of the rough sets methodology[5]. They accept a two dimensional table in an attribute-value format whose rows represent objects of interest (e.g. cases of different design solutions for wind bracings) in terms of attribute values. The user can subsequently analyze the dependency between a selected group of "condition" attributes and a "decision" attribute. The condition attributes usually reflect some important features of the objects whereas the decision attribute typically represents an outcome of the interest, the unit steel weight of the wind bracing in our case. The dependency analysis is done entirely automatically by the system. The dependency can be either functional or probabilistic in nature. The result of the analysis is a collection of simple logical expressions in the form of minimized production rules i.e.: If <condition> then <decision>, which have probability p added in the case of DataLogic system producing probabilistic rules. The simplicity and the "strength" of the rules expressed as number of matching table rows are usually proportional to the degree of the relationship existing between condition attributes and the decision attribute. Although, because of poor quality of data it many happen that not all the identified rules are strong or useful, the system presents the user with a collection of potentially valuable discovered logical patterns which, otherwise, left unnoticed. The discovered "rules" are subject to further improvement and verification, and can be treated as machine-generated hypotheses about properties of population of all potential objects belonging to a specific domain.

4 Knowledge Acquisition

The experiments with learning tools have been conducted using the collection of 376 examples of optimal, minimum weight designs of wind bracings in steel

Learning System	336 examples	374 examples
ROUGH	41	49
DataLogic	3	4

Table 2: Comparison of Number of Decision Rules

skeleton structures of tall buildings. Individual examples represented various types of wind bracings in the height range of 6 to 30 stories, and all wind bracings were designed under the identical assumptions for the same three-bay skeleton structure of a tall building. All examples were prepared using SODA, a computer software system for the analysis, design, and optimization of steel structures.

Two learning systems were used as knowledge acquisition tools, which are described in the Section 3, "Knowledge Acquisition Tools". Both learning systems were used to produce decision rules from two collections of examples. The first collection contained 336 examples, while the second one - 374 examples. The first collection was prepared in the Civil Engineering Department at Wayne State University during the last two years, while the second one was created adding to the available examples another 38 examples, which were developed as a part of the research reported in this paper.

Two experiments were conducted with each learning using both collections of examples. The comparison of the numbers of decision rules obtained in individual cases is given in Table 2.

In terms of the number of decision rules, there is a significant difference between results obtained using ROUGH and DataLogic. The first system produces only deterministic rules, and therefore a large number of such rules is necessary to deal with a complex engineering problem. DataLogic, however, has an ability to produce probabilistic rules, which are valid only for the majority of examples, but are much simpler and easier to interpret than deterministic rules. For example, when decision rules for the determination of the normalized steel unit weight are considered for the attribute nominal value **HIGH**, the following results were obtained:

ROUGH System:

Unit Steel Weight (Attribute H) = HIGH
if:
Attribute B = 2 and
Attribute D = 1 or D =3
Attribute A = 1 or A =5
Attribute E = 1 or E = 2 or E=3

DataLogic System:

Unit Steel Weight (Attribute H) = HIGH
if:
Attribute A = 1 and
Attribute F = 1

The interpretation of the first decision rule is quite complex. The second rule is valid only in 68% of cases considered, but its engineering interpretation is quite simple: in the case of a 6-story skeleton structure with wind bracing in the form of a rigid frame, the heigh steel unit weight should be expected.

At present, the available results are insufficient to identify all engineering advantages and disadvantages of the deterministic and probabilistic decision rules. However, our initial experience indicates, that both types are useful for the decision making purposes. The probabilistic decision rules could be particularly useful when the time factor is involved and only "rough classification" is sufficient.

5 Knowledge Verification

Knowledge produced as the result of all four experiments has been verified using the overall empirical error rate as an estimator of the actual error rate for the entire population of examples. This error rate was found particularly appropriate for the engineering applications of machine learning[1], and it provides the most global evaluation of the knowledge produced. The overall error rates were calculated using the "Leave-One-Out" resampling method, in accordance to the technique described in [4] for the decision rules produced by ROUGH. The error rate was 4.5% for 336 examples, and 13.3% for all 374 examples considered.

In the case of experiments reported, the error rates were significantly worse for the larger collection of examples, and this result was unexpected. However, the close examination of examples revealed, that the collection of 38 examples prepared as a part of our research, and which were added to an existing collection of examples, contained several incorrect examples. These examples affected the quality of the decision rules produced, and resulted in the relatively poor error rates.

6 Conclusions

The conducted feasibility study demonstrated the applicability of the rough sets-based learning systems to learning conceptual design rules. The domain in which experiments were conducted is particularly complex and it is still poorly understood. However, the results of learning in the form of decision rules are acceptable for the domain experts, and the formal verification of the obtained knowledge indicates that the rough sets-based learning of design rules should be useful for a large class of design problems. Much more research should be conducted to study the deterministic versus probabilistic decision rules in the context of engineering, and this work is planned.

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