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Machine Learning in Engineering Design

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Abstract. This paper discusses machine learning in engineering design knowledge acquisition. To illustrate the use of machine learning in design, two knowledge acquisition processes are described in the area of conceptual design of wind bracings in stell skeleton structures of tall buildings. These processes were conducted on examples prepared by experts and on examples representing optimal (minimum weight) designs which were generated by SODA, a computer system for the analysis, design, and optimization of steel structures. All experiments were conducted using DataLogic, a learning system based on the theory of rough sets. The development of the representation space for both collections of examples is discussed. Also, the examples of decision rules produced are given and their verification, based on the overall empirical error rate, is reported. The paper contains also conclusions and suggestions regarding future research on applications of machine learning to knowledge acquisition in engineering design.

1 Introduction

Machine learning in engineering can be used for design knowledge acquisition to acquire formal knowledge for the use in various knowledge-based design support tools. However. the practical engineering applications of machine learning are still difficult, if not impossible, for several reasons, including limited experience, the lack of a methodology for the use of machine learning in knowledge acquisition, and because only few demonstration projects on design knowledge acquisition have been conducted. Therefore, research on machine learning in design knowledge acquisition was initiated by the author in the mid-80's. Its objectives are to study various forms of machine learning in engineering design and to determine their feasibility, including the advantages and disadvantages of the individual learning algorithms and learning systems based on them.

The research is conducted using examples and background knowledge from the area of structural engineering. This area was selected because of the author's experience and because of the general technical reasons. Structural engineering is a subarea of civil engineering whose subjects are various structural systems of buildings, bridges and other civil engineering objects, modeling of their behavior, and analysis and design. Structural engineering as a science has been under development for more than hundred years, and significant knowledge has been acquired in this process. This knowledge is available as various formal theories, e.g., the theory of elasticity, the theory of plasticity, etc., and as examples of actual designs, and it can be converted into formal knowledge-based design support tools. Because of the abundance of existing design examples and the relative ease to prepare additional examples for research purposes, structural engineering is an excellent testing environment for machine learning in design knowledge acquisition and any methodological results obtained in this area should be relevant to other similarly developed engineering areas, as for example, mechanical or chemical engineering.

Engineering design involves the conceptual and detailed design stages. In the conceptual design stage, all needs, constraints, and available knowledge are used to produce a class of design concepts, i.e., abstract descriptions of the engineering system being designed. This design stage is usually conducted in an informal way, and the designer's experience is used to find concepts. These concepts are then analyzed, designed, and eventually optimized in the detailed design stage, where the final design is developed. Present engineering design practice can be characterized by five distinct features concerning knowledge and computer programs for design:

1. All commercial computer programs are based on behavioral models from available formal theories.
2. All computer programs are for the detailed design stage.
3. Knowledge in the form of examples, or extracted from examples, is usually not utilized.
4. No commercial computer programs are available to support the conceptual design stage.
5. Conceptual design requires more abstract knowledge than available behavioral models.

This situation requires improvement for two reasons. First, the conceptual design stage is crucial for the quality of the final design. Therefore, the development of design support tools for conceptual design is important not only from the research point of view, but will also have a significant practical impact. Next, computer systems for analysis, design, and optimization in the detailed design stage are relatively easy to apply, and therefore their use often results in insufficient attention being paid to the conceptual design stage. As a result, design concepts are often developed, or selected, without sufficient understanding of the entire design problem, including knowledge available in the form of examples of earlier designs. This problem is particularly acute when inexperienced designers use design and optimization computer systems; their lack of experience in the form of abstract knowledge may lead them to design of structural systems which could be significantly improved through simple changes in the design concept, for example, changes in the structural configuration.

At present, the development of knowledge-based design support tools for conceptual design is feasible. However, abstract knowledge about conceptual design of engineering systems must be acquired, and this is a majorproblem. Traditional methods of knowledge acquisition are insufficient in complex engineering domains [14], and this knowledge acquisition bottle-neck has already delayed the development of knowledge-based tools for conceptual design. Therefore, automated knowledge acquisition is considered the possible solution, and a number of research projects on automated acquisition of conceptual design knowledge have been recently initiated. Also, in computer science research on machine learning has led to the development of a number of both experimental and commercial learning systems, that means computer programs which use machine learning methods to produce decision rules from examples of previous decisions. Such systems are particularly appropriate for design knowledge acquisition because of the complexity of engineering design and the availability of a large number of evaluated examples of previous designs. The use of decision support systems based on rules is also much more convenient and convincing for engineers than of the systems based on subsymbolic learning, such as genetic algorithms [7, 9] or neural networks [8], particularly that knowledge in the form of rules is "transparent", and can be easily comprehended by the system's users.

There have been several previous studies on the application of machine learning to knowledge acquisition. Gero [10] used an experimental learning system based on a decision tree learning algorithm (ID3) to acquire architectural design knowledge. Reich [19, 20] implemented BRIDGER, an application of the clustering algorithm CLUSTER. BRIDGER was used to acquire bridge design knowledge. Reich and Fenves also studied knowledge acquisition for floor system design in buildings [21] using an experimental system based on the learning system SOAR. Mather has been working on automated acquisition of preliminary design knowledge [12] in which conceptual clustering is augmented by numerical methods of linear regression analysis and probabilistic approaches to pattern identification. A genetic algorithm was used by Grierson and Pak [9] in a system for the optimization of configurations in the conceptual design of skeletal structures and by Hajela for structural synthesis [7]. ROUGH, a learning system based on the theory of rough sets [16, 17], was used by Arciszewski and others [3, 15] for design knowledge acquisition in the area of structural design of wind bracings in tall buildings. Garrett and Ivezic [8] describe an experimental learning system, NETSYN, based on a connectionist learning approach, for the acquisition of conceptual design knowledge. Also, Adeli and Yeah [1] used a neural network to learn engineering design principles. Whitehall, Stepp and Lu [24] applied machine learning to design knowledge acquisition using several experimental learning systems. The AQ15 and AQ17 learning systems, employing the STAR methodology [13], were applied by Arciszewski [15] for learning design rules in the area of conceptual design of wind bracings in steel skeleton structures of tall buildings.

The research reported here was initiated in the mid-80's. This particular area of structural engineering was selected for the experiments for several reasons. First, it is a continuation of research on the analysis and design of wind bracings in tall buildings, initiated by Arciszewski in the early 70's. This research resulted in a good understanding of the tall buildings domain, in the general classification of wind bracings [2], and in the development of the initial representation space, as discussed in Section 3, Development of Representation Space. The former Ph.D. student at Wayne State University, Mohamad Mustafa, who was also involved in the research, has experience directly related to the design of wind bracings in tall buildings. This strong domain background made the research easier and less dependent on other domain experts. Second, designing tall buildings is one of the most complex domains of structural engineering, and designing of the wind bracings i particularly difficult and time-consuming. At present, the analysis, design and optimization of wind bracings in stell skeleton structures can be conducted using computer design and analysis packages such as SODA, STAAD III, etc. The use of these packages makes the detailed design of wind bracings easier, but it still does not eliminate the need for a paper conceptual design, understood here as the selection of the right wind bracing type for a given design case. This selection must be based, as before, on the designer's experience, and therefore acquisition of conceptual design knowledge and its utilization in decision support tools is a challenge which has to be met if there is to be progress in both tall buildings design and civil engineering computing.

The learning system DataLogic [18] was selected for the study for several reasons. Good cooperation has been established between the author and REDUCT System, Inc. of Regina, Canada. This company has been supportive of machine learning research in engineering, and has provided the author with a number of experimental and commercial learning systems. Over the period of the last several years, good methodological experience has been built up in the use of these systems. They are user-friendly and they were developed to meet the research and practical needs of engineers. The final decision to use DataLogic in the study was based on the single fact that it is the first commercial learning system known to the authors which has a built-in component for automatic knowledge verification. Formal knowledge verification was absolutely necessary in the project because of its pragmatic objecive. Therefore, DataLogic was particularly attractive for the research reported here.

2 Knowledge Acquisition Process

The research is a continuation of earlier work by the author and Mohamad Mustafa on automated knowledge acquisition in the conceptual design of wind bracings in tall buildings [15] and on a general engineering methodology of automated knowledge acquisition [4]. Therefore, when this project was initiated the author had a good understanding of both the domain and the methodology of automated knowledge acquisition. For this reason, no extensive domain and methodological studies were necessary to begin knowledge acquisition, which was planned as a five-stage process:

1. Methodological preparation.
2. Development of the representation space.
3. Preparation of examples.
4. Learning decision rules.
5. Knowledge verification.

The first stage, Methodological Preparation, was relatively easy. Domain knowledge was available, and DataLogic was similar to the software used in the previous learning experiments, which were conducted with various rough sets-based learning systems. The major decision as this stage was to purpose a two-track knowledge acquisition, which would be based on the use of two different collections of examples dealing with the same problem of conceptual design of wind bracings in tall buildings. The reason for this was twofold. In the earlier research [15], only examples manually prepared in cooperation with domain experts were used. These examples might contain some misclassifications, which were very difficult to find considering their subjective nature. Also, such complex decision rules were obtained that they were difficult to interpret and verify by the domain experts, and, since no formal verification was conducted, the results of the earlier study were inconclusive. For these reasons, it was decided to make two significant improvements in the research. First, it was concluded that a collection of computer-generated examples would be necessary and that these examples should be both objective and verifiable. Second, it was decided to repeat the earlier work with expert-generated examples, this time using DataLogic, which has an automated knowledge verification capacity. As the result of decisions made in the first stage, all the remaining stages were conducted as two-track stages. In each parallel process of knowledge acquisition, a different collection of examples was used: expert-prepared and computer-generated examples. All these stages and their results are described in the sections three through six.

3 Development of Knowledge Representation Space

In the case of expert-prepared examples, the representation space developed earlier and reported in [15] was used. It was based on a nine-attribute description of a wind bracing in a three-bay steel skeleton structure, which was proposed by Arciszewski [2, 3] for the classification of wind bracings. These attributes describe the individual structural components of a wind bracing and therefore define its type. This multi-attribute description was necessary to discriminate among all types of wind bracings which are presently used in steel skeleton structures. This initial description was expanded by the two nominal attributes. These attributes were added to identify the recommended lower (attribute ten) and upper (attribute eleven) height range for a wind bracing type which is defined by first nine attributes. The attributes and their nominal values used in this representation space are shown in Table 1.

In the second case of computer-generated examples, not all types of wind bracings were considered. Because of the computational limitations of SODA, only a relatively small class of truss and frame bracings could be analyzed, designed, and optimized, and examples produced. Therefore, some attributes were irrelevant for the class of wind bracings considered, and they were eliminated. However, some additional attributes had to be added to cover important design factors which might affect the results of an actual structural design. For example, The *Importance Factor* was added, which represents the effect of wind zone on the structural design. Also, the *Steel Unit Weight* attribute was introduced, which represents the nominal goodness of a given structural design as measured by the relative unit weight of the wind bracing structural system, considered with

Table 1. Knowledge representation for expert-prepared examples

Attributes	Attribute values						
1. static character of joints	rigid	hinged	rigid &				
2. number of bays used by bracing	1	2	2				
3. Number of vertical trusses	0	1	2	3			
4. Number of horizontal trusses	0	1	2	3			
5. Number of horizontal truss systems	0	1	2	3			
6. Core material	none	steel	concrete				
7. Number of cores	0	1	2				
8. Structural character of external members	column s and beans	cables	Shear frames				
9. Static character of bottom external joints	none	rigid	rigid & hinged				
10. Minimum recommended height	<10	10-16	16-24	24-32	32-40	40-60	>60
11. Maximum recommended height	<10	10-16	16-24	24-32	32-40	40-60	>60

respect to other wind bracing design examples of the same height. This modified description of wind bracing in terms of nominal attributes and their values is given in Table 2.

Each example has three major components: 1) a description of the building for which a given bracing is designed (design case or design requirements), 2) a description of the wind bracing structural system, and 3) an evaluation of the structural worth of this system measured by the unit weight of steel. Design requirements are identified by the first three attributes, attributes four through seven describe the structural system of wind bracing itself, and the last attribute, *Steel Unit Weight*, identifies the unit weight of stell of a given wind bracing. This last attribute was converted from an interval into a nominal attribute. The actual steel unit weight range of variation was determined for each building height considered in our study, and the unit weights of individual wind bracings normalized. Next, the normalized (0,1) range was divided into three equal subranges and nominal assigned to these subranges: *low*, *medium*, and *high*, which represent the relative unit steel weight of a given wind bracing type in respect to other types designed for a given building height. For example, *Low* means the low relative unit steel weight which is in the range of variation 0-0.33, while *High* means a high relative unit steel weight for a given wind bracing type under a given set of design requirements, in the range of variation 0.66-1.0. The nominal value "infeasible" means that for a given design case a particular considered type of wind bracing cannot be used for structural reasons.

Table 2. Representation space for computer-generated examples

Attributes	Attribute values				
1. Number of stories	6	12	18	24	30
2. Bay length (feet)	20	30			
3. Importance factor	1.07	1.11			
4. Static character of joints	rigid	hinged	rigid & hinged		
5. Number of bays used by bracing	1	2	3		
6. Number of vertical trusses	0	1	2	3	
7. Number of horizontal trusses	0	1	2	3	
8. Steel unit weight	low	average	high	infeasible	

4 Preparation of Examples

In the first case of expert-prepared examples, individual types of wind bracings were discussed with the selected domain experts. As the result of these discussion of these discussions, two collections of examples, each of 164 cases, were prepared. Each example in the first collection contained a description of a type of wind bracing which is represented in this example (independence attributes) and the lower bound for its height range, which was represented by the decision or dependent attribute. This recommended height range was arbitrarily prepared and was based mostly the domain understanding and experience. Similarly, the second collection of examples contained the same types of wind bracings, but the decision variable represented the upper bound for wind bracing types, also subjectively assumed. For instance, for a wind bracing in the form of a one-bay rigid frame with one horizontal truss situated at the top, the following two examples were prepared:

Example No. 1

WHEN:

* the static character of the joints of a wind bracing (attribute 1) is rigid,
* the number of bays entirely occupied by bracing (attribute 2) is one,
* the number of vertical trusses (attribute 3) is zero,
* the number of horizontal trusses (attribute 4) is one,
* the number of horizontal truss systems (attribute 5) is zero,
* no cores material is to be used (attribute 6),
* the number of cores (attribute 7) is zero,
* the structural character of the external elements (attribute 8) is columns and beams,

* the static character of the external joints (attribute 9) is hinges

THEN:

the minimum recommended height (attribute 10) is less than ten stories.

Example No. 2

WHEN:

* the static character of the joints of a wind bracing (attribute 1) is rigid,
* the number of bays entirely occupied by bracing (attribute 2) is one,
* the number of vertical trusses (attribute 3) is zero,
* the number of horizontal trusses (attribute 4) is one,
* the number of horizontal truss systems (attribute 5) is zero,
* no core material is to be used (attribute 6),
* the number of cores (attribute 7) is zero,
* the structural character of the external elements (attribute 8) is columns and beams,
* the static character of the external joints (attribute 9) is hinges

THEN:

the maximum recommended height (attribute 11) is greater than ten and less than 16 stories.

In the second case of computer-generated examples, the preparation of 366 examples was much more complex. In this case, each example represents a minimum-weight (optimal) design of wind bracings in the steel skeleton structure of tall buildings. All examples were prepared under identical design assumptions for a three-bay skeleton structure. An eight-attribute description of the design problem and the wind bracing itself was used, which is discussed in Section 3. The attributes used are sufficient to describe various types of planar frame, truss, and truss-frame bracings (braced rigid frames) which are appropriate for buildings in the six- to thirty-story height range considered in our study. This limitation on the height of the buildings analyzed in our study was necessary due to the limitations of our software and hardware used for the generation of xamples. All detailed design assumptions regarding loads, dimensions, steel grade, etc. were determined in cooperation with practicing engineers. Actual minimum-weight designs were produced using SODA, a computer system for the analysis, design, and optimization of steel structural systems. The preparation of these examples was extremely time-consuming, and it took nearly two years to complete this stage of the knowledge acquisition process. An example of a minimum weight design of a wind bracing in the form of a rigid frame is shown below:

Example:

* For a six-story office building (attribute 1),
* with a narrow bay length of twenty feet (attribute 2),
* located in an area where the importance factor of the wind (attribute 3) is 1.07,

* the design of a one-bay (attribute 5) wind bracing system

composed of the following structural components:
* static character of joints (attribute 4) is rigid.
* the number of vertical trusses (attribute 6) is zero.
* and the number of horizontal trusses (attribute 7) is zero

THEN:

high steel unit weight (attribute 8) is expected.

5 Learning Decision Rules

Learning was conducted using the commercial system DataLogic, which was developed by REDUCT Systems, Inc. of Regina, Canada. DataLogic is a general-purpose software system for automated knowledge acquisition and for building classification expert systems. The learning component of the system is based on a learning methodology derived from the mathematical theory of rough sets [16. 18]. Two learning processes were conducted. In the first process, expert-prepared examples were used which concerned various types of wind bracings and their lower recommended height ranges. In the second case all computer-generated examples were utilized. In both case the same learning strategy was followed: all examples were used at once, and only the final results were considered.

An example of a decision rule produced is given below:
Decision Rule:

IF:

* the number of bays entirely occupied by bracings in three.
* the number of vertical trusses is zero,
* the number of horizontal trusses is one or two.

THEN:

the minimum recommended height range is ten to sixteen stories.

Structural Interpretation: A wind bracing system composed of a three-bay rigid frame with one or two horizontal trusses is recommended by experts for buildings in the height range of ten ti sixteen stories.

As the result of learning conducted on expert-prepard examples, 68 decision rules were produced. These rules were difficult to interpret, and some were even incorrect from the domain point of view. This result was no surprise. because it was expected that the examples would be insufficient, considering the number of attributes and the domain complexity. Also, errors of misclassification in some examples were suspected, but because of their subjective nature these errors could not be easily found. An example of a decision rule proceduced is given below:

Decision Rule:

IF:

* the number of bays entirely occupied by bracings is three,
* the number of vertical trusses is zero,
* the number of horizontal trusses is one or two.

THEN:

the minimum recommended height range is ten to sixteen stories.

Structural Interpretation: If a wind bracing system composed of a three-bay rigid frame with one or two horizontal trusses is to be used, it is recommended by experts for buildings in the height range of ten to sixteen stories.

In the case of computer-generated examples, forty decision rules were obtained. These were divided into four categories: ***Recommendation Rules, Standard Rules, Avoidance Rules, and Infeasibility Rules.*** The division was based on the nominal value of the decision attribute ***Unit Steel Weight.*** For ***Recommendation Rules*** this value was ***low***, and it indicated the low normalized unit steel weight, which was between 0 and 0.33. These rules, then represent various combinations of independent attributes and their values (design rules) which are associated with the most desirable (lowest) weight of wind bracing. For ***Standard Rules*** the nominal value of the decision attribute was ***average***, and the value of the normalized unit steel weight was between 0.33 and 0.66. These decision rules are associated with the average weight of wind bracing. In the case of ***Avoidance Rules***, the nominal value of the decision attribute is ***high***, and the actual value of this attribute is between 0.66 and 1.0. These rules, then, identify all combinations of independent attributes and their values which should be avoided, because they are associated with the least desirable (highest) weight of bracing. ***Infeasibility Rules*** identify combinations of independent attributes and their values for which no feasible designs could be produced by SODA under present assumptions regarding dimensions, loading, steel grades, etc. One decision rules of each category is shown bellow:

Recommendation Rule

IF:

* the number of vertical trusses is one, two or three,
* the number of stories is greather than or equal to twelve and less than or equal to thirty stories

THEN:

a low unit steel weight of wind bracing should be expected.

Structural Interpretation: When wind bracings with vertical trusses are used in buildings of twelve to thirty stories then a low unit steel weight of wind bracing should be expected.

Standard Rule

IF:

* the number of stories in greater than twelve stories,
* the number of bays entirely occupied by bracing is three,
* the number of vertical trusses is zero,
* the number of horizontal trusses is zero, one or two,

THEN:

an average unit steel weight should be expected.

Structural Interpretation: When designing three-bay wind bracings without vertical trusses and with maximum of two horizontal trusses for buildings with the number of stories greater than twelve, then an average unit steel weight of wind bracing is expected.

Avoidance Rule

IF:

* the number of stories is greater than or equal to eighteen stories,
* the bay length is less than or equal to twenty feet,
* the number of bays entirely occupied by bracing is one,
* the number of vertical trusses is zero,
* the number of horizontal trusses is one or two.

THEN:

a high unit steel weight of bracing should be expected.

Structural Interpretation: When designing buildings in the height range of eighteen to thirty stories with narrow bays with a one-bay wind bracing system with one or two horizontal trusses and with no vertical trusses, then a hight unit weight of steel in wind bracing should be expected.

Infeasibility Rule

IF:

* the number of stories is thirty,
* the number of bays entirely occupied by bracing is one,
* the number of vertical trusses is zero.

THEN:

wind bracing will be infeasible.

Structural Interepretation: In the case of a thirty-story buildings with a one-bay wind bracing systems, any wind bracing without vertical trusses will be infeasible.

6 Knowledge Vertification

The knowledge acquired in the form of final decision rules was verified using the overall empirical error rate calculated by the leave-one-out resampling. The overall empirical error rate is defined as:

$$\text{Eov} = \text{number of errors}/\text{number of tests},$$

where: An error is a misclassification of a testing example, and the number of tests is the number of classification tests.
In the case of the leave-one-out cross validation, one example is removed from the collection of examples and is used for testing, while the remaining examples are used for learning. The resampling is repeated for all examples from a given collection of examples, and the final error rate is calculated as an average for tests conducted on all examples [5, 23].

The final values of the overall empirical error rates for both collections of examples, expert-prepared and computer-generated, are shown above in Table 3.

Table 3. Overal error rates, the leave-one-out cross-validation, expert-and computer-generated examples.

	Error Rates
Expert prepared examples	40
Computer-generated examples	4,75

A significant difference between to overall empirical error rates produced on decision rules extracted from the two collections of examples can be observed. A 40 percent error rate for the decision rules generated from the expert-prepared examples indicates that the learning process was far from completion and that the number of examples used was insufficient to complete the learning process. In contrast, a 4.76 percent error rate for the decision rules extracted from computer-generated examples indicates that the learning process was close to completion when terminated.

7 Conclusions

The feasibility study reported here was the first of its kind in the area of tall building design. Therefore, significant effort went into the development of the representation space and of the methodology of automated knowledge acquisition, including verification of the knowledge acquired. Also, much more time than expected was necessary to prepare the collection of computer-generated examples used in our research.

In the case of expert-prepared examples, the decision rules produced are interesting, and provide a good glimpse into experts understanding of the conceptual design of wind bracings in tall buildings. However, these decision rules are inconsistent, and this clearly demonstrates the insufficiency of the examples used to produce completely useful results. This was expected, considering the number of examples compared to the number of attributes and their nominal values, and the complexity of the problem being analyzed. In the second case of computer-generated examples, the knowledge acquisition process produced a class of decision rules which are clear and could be used as directives in the area of conceptual design of wind bracings for all tall buildings whose design requirements are within the representation space considered. These rules could also be used as heuristics for other design cases, but their general applicability has yet to be determined.

A significant difference was observed between the overall empirical error rates produced on decision rules extracted from two collection of examples: 40 percent versus 4.76 percent. This difference demonstrates the importance of the representation space and the number and quality of examples in automated knowledge acquisition in engineering. It also shows that the rules of learning can be very good in terms of the empirical error rates, and this is especially encouraging for research on the applications of machine learning in engineering. Therefore, it could be concluded that learning systems are useful knowledge acquisition tools in engineering, particularly when a sufficient number of "clean" examples is used. In this case, good results can be expected in terms of both the comprehensibility of decision rules and the performance of the learning system as measured by the overall empirical error rate.

The study was conducted using a single learning system, DataLogic. Therefore, it is difficult to generalize our methodological results for other learning systems, and more feasibility studies utilizing other learning systems are suggested. It is particularly important to compare and evaluate performance of various learning systems on the same data, with the performance evaluation done using the same methodology and several empirical error rates, including commission and omission error rates [23]. In general, a methodological foundation for using learning systems in engineering should be developed, which would make the practical applications of such systems feasible and would eliminate the need to conduct extensive methodological studies in each case of engineering applications of learning systems.

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