Large and Tall Buildings: A case study in the application of Decision Support and Data Mining

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Abstract. Large and Tall buildings can be broadly classified into three groups: sprawling, squat, or tall. The decision to build a particular type of large building can be based on a large number of attributes. One set of possible values of the attributes represents a building design, which must be feasible. In addition, it is also important to understand how such a set of attributes impacts on the value of the proposed building to the customer – in particular the value of the proposed building design with respect to the client's value drivers. A building construction expert's analysis of seventy international building projects was used as input to decision support and data mining analyses. Decision models were developed that mapped customer values of proposed construction project's attributes. Data mining – on albeit limited examples – was used to model the feasibility of construction projects from their input attributes. On this basis, we propose a novel way of combining Data Mining and Decision Support methods: both techniques are employed to utilise the same input vectors, but one – Decision Support Models – is designed to assess and possibly maximise utility, while the other – Data Mining Models – provides a test for feasibility.

1. Introduction

The expertise of a large number of individuals is required to successfully complete any significant engineering project, including that of constructing a large building. A vast range of skills – including surveying, architectural design, structural engineering, and service facility design – are deployed in the building design phase alone. The very early phase of defining the project scope and broad specification can lead to difficult negotiations with the prospective owner of the building (referred to as the client). The client has a set of preferences about the type of building they desire – which may significantly impact on both the feasibility of the design and the cost of the project. Moreover different clients place different *values* on attributes of the building project.

In the early building specification phase, clients work with construction project experts to settle on a broad building design. This can require the selection of particular building attributes that are feasible, but also maximize the utility of the building for the client. The construction experts need to be able to articulate the complex interaction between the attributes, to help guide the clients to a feasible and valuable design.

1.1 Large and tall buildings, and Value Drivers

The size and shape of a building has a dramatic impact on many aspects including capital cost, ease of design, the use of standard components, programme, logistics and whole life costs which all affect the rate of return to a client. Unlike many other industries, construction is a complex blend of disperate needs, skills and techniques that are difficult to co-ordinate.

The Capital Projects and Facilities Consultants *EC Harris* have recently completed a study examining the value drivers between different shapes of building. In order to understand the interaction between the different shapes and sizes, it was necessary to define 18 "virtual buildings" which are grouped by size (medium, large and very large), shape (squat, sprawling and tall) and finally quality (medium and high). The study of the 18 benchmarks uncovered the knowledge that buildings with 20 storeys are most likely to give the best return on investment.

Although value drivers have been talked about over the years, they have not really been properly accounted for within the construction industry as a whole. Instead, most of the focus in this general area has been on establishing key performance indicators that can be easily measured, a fact that to some extent explains the approach to date.

In order to understand the purpose of undertaking this particular research into value drivers, it is necessary to first look at the fundamental difference between value and performance. Put simply, the value of any aspect of a construction project to a client could be said to be that which would make him very happy and view the project as a success, or perhaps that which would make him dissatisfied with the project outcome. In this sense, if the client was a food retailer considering building a new store, some of his values might include *Cleanliness*; *Time*; *Appearance*; and *Shareholder Value*.

The traditional method within the construction industry for measuring the clients' satisfaction tends to focus on tangible, or measurable attributes that can be directly compared from client to client or project to project and would perhaps include *Time*; *Cost*; *Safety Record*; and *Number of Defects*.

Although value and performance are sometimes the same (e.g. time), EC Harris have been looking at ways in which client value drivers can be met through traditional means. This is what drove the requirement for this research, which above all was intended to identify a method of linking client drivers with building characteristics.

1.2 Data Mining and Decision Support

Data Mining (DM) is a process which utilizes a range of techniques and tools to extract patterns from data. Witten and Fank [9] describe data mining as "solving problems by analyzing data already present in databases". In this work, the *problem* was to analyse the value drivers in the construction of large and tall buildings, and the *database* was a set of buildings. The main objective of the DM task was to investigate the relationship between the attributers of large and tall buildings and their classification into three dimensions: *Size*, *Shape*, and *Quality* (known here as the *SSQ* dimensions).

Decision Support (DS) is a broad field concerned with supporting people in making decisions [1]. In our case, the problem was to evaluate and analyse buildings described by various attributes, and on this basis to select buildings and their characteristics so as to best match the client's value drivers. Such DS problems are addressed within Decision Analysis [3], which provides a suitable methodology: hierarchical multi-attribute modeling. The idea is to develop a model that evaluates available choices (options) giving an estimate of their worthiness (utility) for the decision-maker. In the model, the whole decision problem is decomposed into smaller and less complex subproblems. These are represented by variables, which are organized into a hierarchy. In addition, some rules or procedures are defined that aggregate the evaluation of sub problems into the overall evaluation of options. The development of models is performed in an "expert modeling" way, which means that they are hand-made by an expert, possibly supported by a decision analyst and suitable software tools.

1.3 Outline of the remainder of the paper

Section 2 details the problem solving methodology – based on CRISP-DM – and its execution for this project. Much of the process is common between both data mining and decision support, but it does deviate in the modeling phase. Section 3 provides a discussion of the solutions provided, while suggestions for future work are considered in Section 4. Finally, Section 5 presents the conclusions.

2. Problem solving methodology and execution

Data Mining and Decision Support analysis processes broadly consist of a number of phases. Within the Sol-EU-Net consortium [8], the CRISP-DM methodology is used — CRoss Industry Standard Process for Data Mining [2]. In CRISP-DM, six interrelated phases are used to describe the data mining process: *business understanding*, *data understanding*, *data preparation*, *modeling*, *evaluation*, and *deployment*. Many of the phases are useful in both DM and DS problem solving methods.

2.1 Business Understanding

The data analytical problem to be solved must be set in the context of the business from which it is drawn. This is the aim of the *business understanding phase*. The owner of the problem in this work was the Capital Projects and Facilities Consultancy, *EC Harris*, who have offices in over twenty countries. The following quotations are taken from their web site (www.echarris.com):

> *"EC Harris is a leading International Capital Project and Facilities Consultancy with nearly 1,800 people directly managed and employed on construction and facilities consultancy worldwide. ... We serve clients whose needs span the whole life of a property asset, from setting winning strategies through delivery of the asset and its operation. Performance objectives which reflect clients' needs typically include ... capabilities as a Capital Project and Facilities Consultancy."*

The main objective, from EC Harris' point of view, of this project was to further explore work already undertaken in order to establish or confirm the following with respect to their understanding of the construction of large and tall buildings:

- That the work done to date was essentially sound and valid.
- To explore different ways of looking at the existing data and potentially discover new links between the various attributes of large and tall buildings.
- That it was reasonable and realistic to assume that client's value drivers could be linked to building attributes.
- To establish a method of linking client values with tangible attributes.
- That client satisfaction could probably be increased by establishing and respecting which building attributes most closely related to their values.
- To create a concept model that could be further developed as a discussion and decision support tool with clients. This would be used to establish clients value priorities, translated into building attributes, at a very early stage in the project.
- To explore the use of DM and DS as techniques for wider use in future projects.
- To explore whether subjective client views (values, which are largely tacit) could be extracted and linked to tangible attributes such as the height of a building.

An existing decision support tool focusing on large and tall buildings had already been developed at EC Harris. This tool is based on expert analysis of seventy buildings, as well as the combined expertise from within the EC Harris organization. The approach was to produce a set of *typical* or *benchmark* buildings for the space of the SSQ dimensions, which can be seen as an 18 cell cube (pictured in Figure 1).

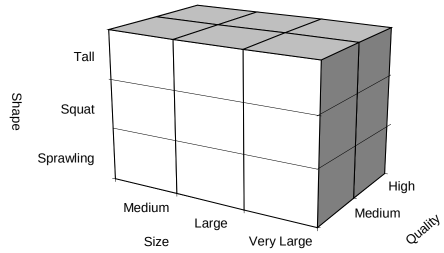


Figure 1 The Size-Shape-Quality Cube (SSQ)

2.2 Data Understanding

The purpose of the data understanding phase is to become familiar with all sources of the data. For this problem, the data was delivered in the form of a spreadsheet. This contained a set of building construction project attributes, 18 benchmark buildings, and 70 further real building projects. The following is a list of the categories of building construction project attributes, with the number of items in parentheses: *Location* (9), *Function* (6), *Description* (16), *Capacity* (*Building*) (36), *Capacity (Services)* (15), Cost (100), *Procurement* (2), *Programme* (5), *Access & Safety* (6), *Whole Life* (2), *Appearance* (4), *Project Team* (10). For each of the buildings (18 benchmark, and 70 real) values to the above attributes were provided.

Data relating to the value drivers were also provided in the spreadsheet (hereafter referred to as *attribute/value-driver matrix*, AVDM). For each of the building attributes, a series of value dimensions were available, with respect to three different client types: *Developer*, *Government*, and *Owner-occupier*. These value attributes were classed in to three categories: **Financial** (Profit, Shareholder Value, Market Value, Growth), **Process** (Risk Control, Quality, Standards, Safety, Best Practice, Innovation, Supply Chain, Reuse of Resources, Whole Life), and **Market** (Image, Flexibility, Occupants Needs, Public Perception, Environmental Impact). AVDM is further explained in section 2.4.2, and a part of AVDM is shown in Table 2.

2.3 Data Preparation

The data preparation phase covers all the activities for constructing the final data sets for the modeling tools.

For DM, the following data preparation was performed. The main objectives of the DM were to (1) perform exploratory data analyses, and (2) to establish models between the building construction attributes and the SSQ dimensions – this was focused on the 18 benchmark building cases. Data preprocessing was aimed at reducing the number of attributes from the 211 attributes. With respect to the benchmark records, there were many attributes that did not discriminate on any of the SSQ dimensions. The attributes were sorted into three categories as follows: *Non-discriminating* means that the attribute values did not change, *Functionally dependent* were those attributes which were functionally dependent on other attributes (as they were formulae in the spreadsheet), and *Discriminating* attributes had values that varied. The discriminating attributes from the above (numbering 47) were all selected for the DM data set.

2.4 Modeling

The modeling techniques used by Data Mining and Decision Support differ sufficiently that they can be considered separately.

2.4.1 Data Mining Modeling

Three DM approaches were used in the modeling process: Clustering; Automatic attribute subset selection; and Decision tree induction.

Basic clustering. There was an implicit assumption from the domain expert that the benchmark buildings could be grouped into clusters. To test such a hypothesis, clustering was performed on the records of the 18 benchmark buildings. Weka's [9] KMeans implementation was used with three clusters selected. Studying the cluster numbers versus various attributes, lead to the tentative conclusion that the clusters seemed to separate based on Building Size.

Automatic attribute subset selection. Weka was used to determine further whether the attributes could be reduced. This was performed with respect to each of the SSQ Cube dimensions: Size, Shape, and Quality. (No results are reported here.)

Decision tree induction. The aim of this modeling was to produce – if possible – simple decision trees to map attributes into each of the SSQ dimensions. For this, the Weka implementation of C4.5 [7] – J48 – was deployed. Given the limited data, J48 was used with no test set (only using the 18 benchmark buildings as both the training and test sets), with validation only on the training set. The basic scheme was weka.classifiers.j48.J48 -C 0.25 -M 2, using 18 records and 63 attributes. The approach was to determine which attributes were selected by J48 as significant. For further runs, those attributes that were significant in previous runs were excluded to highlight the next level of significant attributes. Sample results for each of the three target dimensions of *Size*, *Shape*, and *Quality* are summarized in Table 1. The trees induced were typically very concise. The results were discussed with the expert who was able to interpret each of the trees in light of his knowledge. A number of trees provided new insights into the relationships between the building attributes.

Table 1 Sample results of decision tree induction for the SSQ dimensions

<table>
<tr><th>Target</th><th>Result</th></tr>
<tr><td>Size</td><td>B6 “Flexibility Rating” <= 3
| B3 “Hours of Building use” <= 12: medium (6.0)
| B3 “Hours of Building use” > 12: large (6.0)
B6 “Flexibility Rating” > 3: very_large (6.0)</td></tr>
<tr><td>Shape</td><td>D10 “Clear Suspended Ceiling Depth” <= 350
| H3 “Proportion of Prefabrication (Off Site)” <= 2: Squat (6.0)
| H3 “Proportion of Prefabrication (Off Site)” > 2: Tall (6.0)
D10 “Clear Suspended Ceiling Depth” > 350: Sprawling (6.0)</td></tr>
<tr><td>Quality</td><td>L2 “Finishes” <= 3: medium (9.0)
L2 “Finishes” > 3: high (9.0)</td></tr>
</table>

2.4.2 Decision Support Modeling

Three multi-attribute models were developed for the evaluation of buildings. All of them are hierarchical and represent a relationship between a building, described by a set of input variables, and its utility to the client. However, in order to explore various relations between attributes and value drivers, and to experiment with different knowledge representations, the models greatly differ in the:

- selection of input variables, which can be subsets of the attributes, value drivers, or both;
- level of detail in terms of the number of input variables and the depth of hierarchy;
- type of variables used in the model: continuous or discrete;
- relationship between attributes and value drivers: dependent or independent.

In the following, we refer to the models by the names of software packages that have been used for their development: Microsoft Excel [6], HIVIEW [4], and DEXi [5].

Excel Model

This is the most detailed DS model that uses 181 input attributes, which practically represent the whole input set. From the 211 available attributes, we only excluded 30 functionally dependent attributes that are obtainable from other attributes by a multiplication by a constant; these were redundant for this task.

A building project, described by the input attributes, is evaluated by a two-stage linear aggregation procedure, sketched in Figure 2. First, the values of attributes are mapped into 18 criteria, which represent value drivers. In the second stage, these are, according to their own hierarchical structure, aggregated into the overall evaluation. All the variables are continuous and represented on a [0,5] preference scale, where 0 and 5 correspond to the most and the least preferred evaluation, respectively.

The evaluation in both stages is carried out according to the expert-defined attribute/value-driver matrix (AVDM). Basically, this is a 181×18 matrix containing elements $e_{a,v}\in[0,5]$, specifying the expected influence of attribute a to the value driver v; the value 0 indicates no influence, and 5 very important influence. A small fragment of AVDM, which defines the attribute/value-driver relationship for governmental clients, is presented in Table 2. For this type of model, the expert actually developed three such matrices, estimating the typical value drivers for three types of clients: Government, Development, and Owner Occupier.

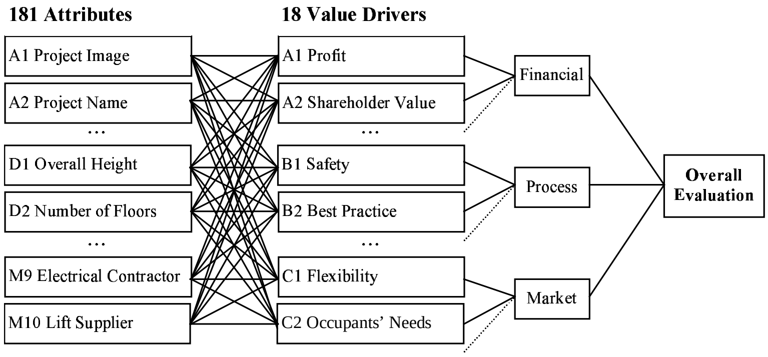


Figure 2 Two-stage evaluation schema of the Excel Model

Table 2 A part of attribute/value-driver matrix for governmental clients

Attributes	Value Drivers					
	Profit	Sharehld. Value	Safety	Best Practice	Flexibility	Occupants' Needs
A1 Project Image	0	1	0	0	1	1
A2 Project Name	0	1	0	0	1	1
D1 Overall Height	0	1	4	4	2	5
D2 Number of Floors	0	1	4	4	2	5

In the absence of dedicated DS software suitable for this kind of two-stage modeling, this model was implemented using Microsoft Excel. Figure 3 shows a few most essential parts of this fairly large spreadsheet – hiding several columns and most of the N=181 attributes. Input to the evaluation is specified in column J by of preferences $p_a \in [0,5]$, defined for each attribute a. There are four essential outputs of the model:

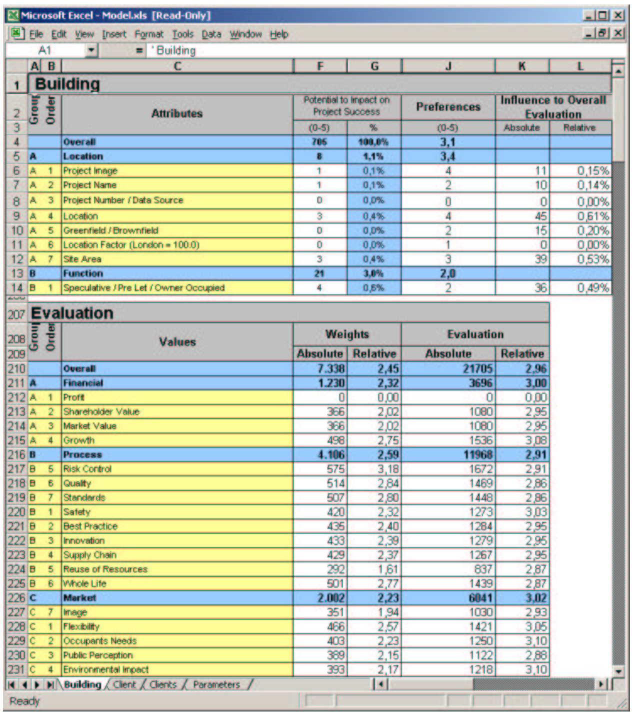
1. *Absolute and relative weights of value drivers* (see Figure 3, columns F and G, rows 210 and below). These are obtained from AVDM. For each value driver v, its absolute weight W_v is defined as

   $$W_v = \sum_{i=1}^{N} e_{i,v}$$

   Relative weights are then proportionally normalised to the [0,5] scale.
2. *Absolute and relative evaluation of value drivers* (columns K and L, rows 210 and below). These are obtained from building's preferences p and taking into account elements e of AVDM. Again, relative evaluation is obtained by normalisation from the following absolute evaluation:

   $$E_v = \sum_{i=1}^{N} e_{i,v} p_i$$

3. *Overall evaluation* (J210, K210): Final estimation of the building's utility to the client. It is obtained by a bottom-up aggregation of individual E_v's weighted by W_v's according to the hierarchical structure of value drivers.
4. *What-if analysis* (columns K and L, rows 5 to 14): For each attribute, it shows how would the change of that attribute by one unit influence the overall evaluation of the building. For example, the improvement of the attribute *A4 Location* from 4 to 5 would improve the overall evaluation by 45 absolute "points" or, in relative terms, by 0.61%.


Microsoft Excel - Model.xls [Read-Only]

File Edit View Insert Format Tools Data Window Help

A1 = 'Building

	A	B	C	F	G	J	K	L
1	**Building**							
2	Group	Order	Attributes	Potential to Impact on Project Success		Preferences	Influence to Overall Evaluation	
3				(0-5)	%	(0-5)	Absolute	Relative
4			**Overall**	**705**	**100,0%**	**3,1**		
5	**A**		**Location**	**8**	**1,1%**	**3,4**		
6	A	1	Project Image	1	0,1%	4	11	0,15%
7	A	2	Project Name	1	0,1%	2	10	0,14%
8	A	3	Project Number / Data Source	0	0,0%	0	0	0,00%
9	A	4	Location	3	0,4%	4	45	0,61%
10	A	5	Greenfield / Brownfield	0	0,0%	2	15	0,20%
11	A	6	Location Factor (London = 100.0)	0	0,0%	1	0	0,00%
12	A	7	Site Area	3	0,4%	3	39	0,53%
13	**B**		**Function**	**21**	**3,0%**	**2,0**		
14	B	1	Speculative / Pre Let / Owner Occupied	4	0,6%	2	36	0,49%

	A	B	C	F	G	J	K
207	**Evaluation**						
208	Group	Order	Values	Weights		Evaluation	
209				Absolute	Relative	Absolute	Relative
210			**Overall**	**7.338**	**2,45**	**21705**	**2,96**
211	**A**		**Financial**	**1.230**	**2,32**	**3696**	**3,00**
212	A	1	Profit	0	0,00	0	0,00
213	A	2	Shareholder Value	366	2,02	1080	2,95
214	A	3	Market Value	366	2,02	1080	2,95
215	A	4	Growth	498	2,75	1536	3,08
216	**B**		**Process**	**4.106**	**2,59**	**11968**	**2,91**
217	B	5	Risk Control	575	3,18	1672	2,91
218	B	6	Quality	514	2,84	1469	2,86
219	B	7	Standards	507	2,80	1448	2,86
220	B	1	Safety	420	2,32	1273	3,03
221	B	2	Best Practice	435	2,40	1284	2,95
222	B	3	Innovation	433	2,39	1279	2,95
223	B	4	Supply Chain	429	2,37	1267	2,95
224	B	5	Reuse of Resources	292	1,61	837	2,87
225	B	6	Whole Life	501	2,77	1439	2,87
226	**C**		**Market**	**2.002**	**2,23**	**6041**	**3,02**
227	C	7	Image	351	1,94	1030	2,93
228	C	1	Flexibility	466	2,57	1421	3,05
229	C	2	Occupants Needs	403	2,23	1250	3,10
230	C	3	Public Perception	389	2,15	1122	2,88
231	C	4	Environmental Impact	393	2,17	1218	3,10

Building / Client / Clients / Parameters

Ready

Figure 3: **An excerpt from the Excel Model**

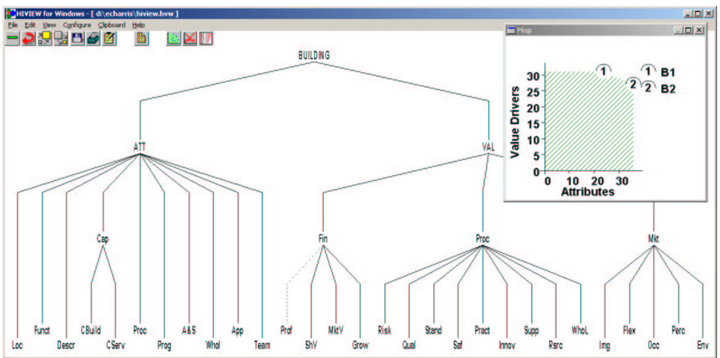


Figure 4: HIVIEW Model: Hierarchical structure of variables and a map

HIVIEW Model
In the second DS model, the aim was to explore a different way of combining attributes and value drivers. Instead of the Excel Model's two-way sequential procedure, they were evaluated in parallel, by combining two hierarchies of preference variables: one consisting of attributes and the other consisting of value drivers. The hierarchy of attributes was defined in less detail than previously, using only 11 top-level attributes (Figure 4). The essential characteristic of this model is that it facilitates a direct analysis of the relationship between attributes and value drivers using maps. Also, HIVIEW provides tools for sensitivity analysis, which are particularly suitable for this problem.

DEXi Model
The third DS model produced is the least detailed one. It involves only value drivers, which are represented by a four-level hierarchy (Figure 5). All the variables in the hierarchy are qualitative, i.e., they assess and evaluate value drivers using qualitative descriptive values, such as: *unacceptable*, *acceptable*, *good*, *excellent*. The aggregation is carried out by expert-defined *if-then* decision rules.

This model is best suited for a quick, qualitative analysis of value drivers, especially when comparing different buildings and their variants. The model supports what-if analysis and can represent evaluation results using radar charts (Figure 5). Furthermore, since DEXi's evaluation mechanism can deal with missing data, this is the only model of the three that can produce results – albeit less precise – even when some client's value drivers are unknown.

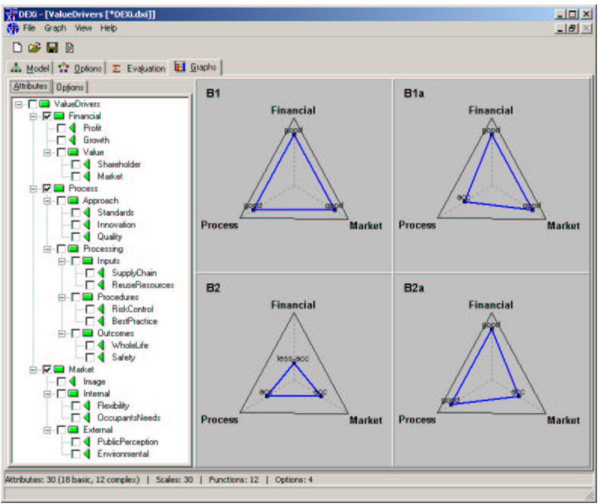


Figure 5: DEXi Model: Hierarchy of value drivers and radar charts

2.5 Evaluation

To date, the evaluation of the models was based solely on feedback from the building construction expert. After the models were presented and discussed, the expert gave the following comments:

"The data mining and decision support techniques used on this project have been extremely valuable to me personally as well as the EC Harris organization and despite the relatively limited pool of data and time available have still added value to the work that we were already doing. The initial expectations have been fulfilled, with the key benefits being;

- *Existing work by EC Harris was validated.*
- *Some new links between attributes were discovered.*
- *Client values linked to tangible attributes.*
- *Concept value vs. attribute model created.*
- *Established potential for future data mining and decision support."*

2.6 Deployment

To date none of the models have been deployed in the EC Harris organization. There are plans to perform further modeling, and potentially deploy some of the models.

3. Discussion

The inputs to this project were data about the construction of large and tall buildings, as well as expert opinion on the values of aspects of these buildings for their owners. The data contained 211 attributes, and of two types of records: (1) 18 expert-assembled benchmark buildings, which were created from experience within the EC Harris organization, and (2) 70 partially complete records of real building construction projects or their designs. It was remarkable that the expert was able to complete the assignment of values to over ten thousand items in less than 24 hours. Furthermore, the analyses of the value data showed that the assignments were reasonably consistent.

The broad goals of the project were to: (1) explore in detail relevant data for further knowledge development; (2) identify and articulate the key issues around value drivers in construction; and (3) build models for use in a decision support system. These objectives were considered to have been achieved by the building expert.

In what follows we highlight some of the achievements of the project.

Attribute mapping strategies. Two main mapping strategies were developed. The first was the mapping building attributes to the evaluation of the building with respect to the client's values. The second was the mapping of attributes to the type of building.

Decision Models with two stages of evaluation. Decision Models were produced that utilized a two state evaluation procedure in which building construction project attributes are mapped to an overall evaluation. This is performed by a two-stage linear aggregation procedure (refer back to Figure 2). First, the values of attributes are mapped into 18 criteria, which represent value drivers. In the second stage, these, according to their own hierarchical structure, are aggregated into the overall evaluation. All the variables in the model are continuous.

Combining Data Mining and Decision Support models. The two mapping strategies, outlined above, were performed using two different analysis approaches. The development of the value drivers models was performed using DS, while the models for mapping attributes to building types were produced by DM. Both of the approaches use (in part) similar input attributes. This gives rise to a novel opportunity to combine the two approaches (Figure 6).

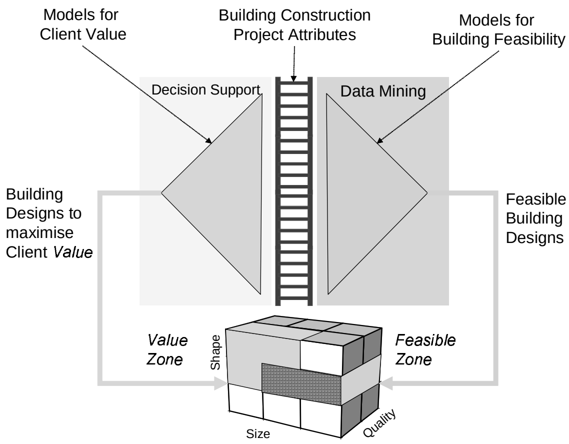


Figure 6 Combining Decision Support and Data Mining Models

The combination of the DM and DS models suggests a development of decision support system to assist clients in choosing their most suitable building type. A client – with the help of a building expert – can articulate his values on the attributes that have been selected. These values can be maximized using the decision support models. Having chosen the attributes, the data mining models can then be used to suggest whether such a building project is broadly feasible. This process can be repeated further until the client is satisfied with a building type.

A generic framework for analysing value drivers for business. The procedure utilized in producing decision models for value drivers could be deployed in other business environments.

4. Future Work

The execution of this project has – as is common – provided many insights, but has also lead to new questions and directions for future work. Some of the directions are specific to the problems tackled in the project, while others have broader applicability. Some directions are listed below.

- Simplification of Models
- Analysis of design constraints and building project feasibility
- Integrating DEXi models with the Excel models
- Establish mappings from Attributes to the preferences of attributes

- Further develop and extend a framework for the generic analysis of value drivers in business.

Due to space constraints, none of these directions are discussed in any detail.

5. Conclusions

The objective of this work was to employ the tools and techniques of two related disciplines – Data Mining and Decision Support – to the solution of the practical problem of knowledge development and articulation in the domain of the building construction of large and tall buildings.

Data Mining techniques produced models that validated existing expert analyses, as well as providing some new insights. Significant models, however, were produced by Decision Support techniques, to be used in optimizing the perceived value of possible building projects by clients. The original modeling objectives were achieved with the possibility of deploying the models within the building expert's organization.

In working on the specific problem, a concept of how data mining and decision support models may be integrated was proposed. In such a setting, the different models utilize similar input vectors, but produce differing outputs. This may give rise to the development of decision support systems that allow the cycling between the states provided by the models until a suitable candidate solution is reached.

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