Costing Issues Regarding Product Variant Design

P. Baguley[1], D. Schaefer[1], and Tom Page[2]
[1]Design and Manufacturing Research Group, School of Engineering
University of Durham, [2] Department of Design and Technology, Loughborough University

Abstract
Competition for most companies means there is a need to offer their products in a number of different variants to their customers. Tools such as computer-aided product configuration systems to automatically compose existing components to new variants of a specific product are widely used today. However, in contemporary CAE tools there is a lack of intelligent mechanisms to consider such aspects, especially in relation to interaction between ECAD and MCAD affects. This paper proposes the use of type-2 fuzzy logic to circumvent such problems in capturing the cost of interactions using Integrated Product Teams.

Keywords:
Costing, optimisation, type-2 fuzzy logic, automation, product configuration

1 INTRODUCTION

ECAD (Electrical Computer Aided Design) is an application of design of electrical equipment. The design of electrical equipment impacts mechanical design of associated components, such as control/switch cabinets, etc. The scope of applications of the interaction between ECAD and MCAD (Mechanical Computer Aided Design) is huge, notably factory design and the design of systems that manufacture products being on the large scale side, while switch cabinets etc. are on the small scale side.

An important issue is the integration of ECAD and MCAD systems within an overall engineering environment. Usually, the electrical and mechanical parts of electromechanical components are designed individually with separate systems. There is no bidirectional modelling incorporating updates on each side. Today, existing multi- or interdisciplinary constraints between electrical and mechanical design parts cannot be modelled properly. Hence, there is no bidirectional constraint propagation etc. The clear complexity of this interaction impacts the complexity of cost models at all stages of the life cycle.

Product configuration and configuration based modelling is a widespread means for the development of product variants in MCAD. Recently, this methodology has been applied to ECAD as well. In ECAD, configuration objects are for instance schematics and diagrams representing particular functional units of an electrical installation. Plans and diagrams refer to parts that may appear on a Bill Of Materials (BOM). Cost knowledge is required for entire installations and all the components the installation is made of, such as assemblies, sub-assemblies, and so on. No previous work has dealt with cost models for the ECAD and MCAD interaction but previous cost models have appeared separately for ECAD and MCAD ([1]). An encompassing cost model including both ECAD and MCAD, i.e. an overall systems model, might give management more opportunities for optimisation and is a growing concern in the design of complex systems.

Therefore it is important for ECAD to have an indicator that communicates the cost of decisions from MCAD and vice versa. Because no previous models have been made in this way, there is also no previous data supporting these types of models. Fuzzy logic is a method which can model quantities using no data, but experts. Fuzzy logic can be categorised into Type-1 and Type-2 fuzzy logic. Type-1 fuzzy logic includes precise degrees of membership to a set, whereas type-2 fuzzy logic includes degrees of membership to a set that are type-1 fuzzy sets themselves. There are very few applications of Type-2 fuzzy logic, despite some clear advantages in modelling accuracy and robustness found by [2]. Type-2 fuzzy logic can be clearly distinguished by its efficacy in a team environment. An application of ECAD and type-2 fuzzy logic can be integrated electronically via spreadsheet or MATLAB files using a Product Data Management (PDM) system with the Computer Aided Design system.

2 EXAMPLE PROBLEM

A company wants to develop an elevator that can carry 10 persons. The elevator has electrical parts as well as mechanical parts and there exist a lot of constraints between them. However, division A of the company develops the mechanical parts with an MCAD system and division B develops the electrical ones with an ECAD system. There is no integration of both systems. Therefore, the corresponding engineers talk to each other in a conventional sense and then continue working with their CAD systems. There is no interdisciplinary concurrent engineering at all, neither in respect to the general engineering nor to costing aspects relevant to management, controlling and other decisions of the company.

Some months later, the same company is asked to develop two variants of their elevators, one for carrying a maximum of 5 persons, one for a maximum of 25 persons. The problem is to develop the two variants based on existing drawings, plans, etc., and to calculate costs.

3 COST MODELLING TYPES

There are a few main types of cost models that are associated with particular stages of the product development cycle. The 2 main examples of this are:

- Grass roots cost models, and
- Parametric cost models ([3]).

Grass roots cost models break down a product into a very detailed Bill Of Materials (BOM) and associated detailed activities. Grass roots cost modelling suffers from resource intensive data collection that can only occur late in the design stage when the detail required is available. In addition, if the detail is available, the large amount of summations involved of the small details can become a significant error in cost. Parametric cost models are those most significant to this research. Parametric cost models relate product specifications to cost. These product specifications can be geometric or functional or other, and typically occur early in the design, for example concept or aggregate (as defined by [4]). Parametric cost models produce relationships between the individual costs of previous variants for which cost estimates exist, and their specifications, identified as "cost drivers". Such relationships are termed Cost Estimating Relationships (CERs) and are typically produced using regression analysis.

4 DATA SOURCES

A key part of cost modelling is in identifying and collecting relevant data from data sources, the part that is the key constraint in subsequent cost modelling tasks. The lack of data informing designers of the bidirectional impact of MCAD with ECAD means cost modelling methods that can operate with no data are essential. Fuzzy logic is one such method that can use expert opinion and intuition to form models. Fuzzy logic that can be used by an Integrated Product Team (IPT), i.e one that can lever expertise in both ECAD and MCAD, is Type-2 fuzzy logic.

5 SOLUTION TO THE PROBLEM

The proposed solution to the problem is to capture the interaction between ECAD and MCAD using expert rules. Such expert rules can be based on the dependencies between design entities, a requirement of parametric modelling in electrical design identified by [5]. With the growing standardisation of parametric parts in both ECAD and MCAD (known as the "box of bricks" in MCAD) a more general set of expert rules can be foreseen applied to the general problem of the interaction between standard parts. For our elevator problem a sample of the set of rules could be:

If "Number of People" is "Large" then "Motor" is "Medium"

If "Motor" is "Medium" then "Motor Cost" is "Small"

If "Motor" is "Medium" then "Cable Strength" is "High"

If "Cable Strength" is "High" then "Cable Cost" is "Very High"

The interactions are captured as expert knowledge in a series of structured look up tables. It is envisaged in the future, when the method will be a mature one, that such tables can be supplied by the manufacturers of electrical equipment. Hence the knowledge becomes a marketable product. This ultimate knowledge capture mechanism within fuzzy logic can be termed that of a grammar ([6]).

6 FUZZY SETS

A central issue surrounding fuzzy logic is that of fuzzy sets. In conventional Boolean thinking elements can belong to a set (represented by the value 1), or not belong to the set (represented by 0). The boundary is very well defined. Fuzzy sets are different in that elements can partially belong to a set to a degree between 0 and 1. Hence a person can belong to the set of tall people (to a degree 0.3) and also to the set of short people (to a degree 0.3). It is noticed that the degrees of membership to the sets of tall people and short people do not necessarily add up to 1. The concepts of tall and short are fuzzy. Fuzzy sets were developed by Zadeh ([7]) because humans do not think in a Boolean sense, so that there is not a well defined barrier between being short and being tall, and in fact any calculations based on a well defined barrier should come under question. Two fuzzy sets are shown in Figure 1, where it is noticed that a person is only thought of as certainly tall (degree of membership 1 to the fuzzy set, tall) if they are 6 foot and over. Of course this is subjective and might be moved higher or lower, or other.

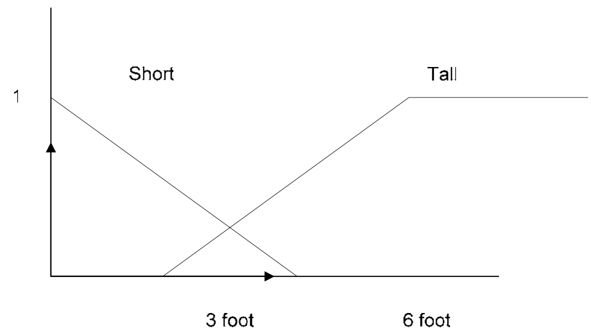

Figure 1: Type-1 fuzzy sets

7 TYPE-2 FUZZY LOGIC

Type-2 fuzzy logic takes the concept of fuzzy sets further by recognising that degrees of membership to a fuzzy set are also precisely defined. Mendel ([2]) and John ([8]) describe how uncertainty is not fully captured by precise degrees of membership since precision implies a form of certainty. Hence type-2 fuzzy logic should be considered as a system when the degrees of membership to a set are fuzzy sets themselves. In addition, when utilising type-2 fuzzy logic, there is the process of type reduction to reduce type-2 fuzzy sets to type-1 fuzzy sets after performing inferencing. (This is an algorithmic concern but also has connotations for the interpretation of uncertainty). Subsequently it is possible to defuzzify the type-1 (reduced type-2) fuzzy set. John ([8]), provides a formal definition from Karnik and Mendel ([9]), "a type-2 fuzzy set is characterised by a fuzzy membership function, i.e. the membership value (or membership grade) for each element of this set is a fuzzy set in [0,1], unlike a type-1 fuzzy set where the membership grade is a crisp number in [0,1]".

8 SEQUENCE OF STEPS IN PRODUCING TYPE-2 FUZZY LOGIC MODELS

The sequence of steps in producing type-2 fuzzy logic models can be summarised (as shown in Figure 2):

1. identify the "concepts" to be used in the model
2. Identify expert rules
3. Produce type-2 fuzzy sets for the concepts in the expert rules using knowledge acquisition methods, or newly developed automatic methods ([10])

4. Identify fuzzy logic operators by consensus from the existing literature, or by using a decision making methodology. A decision making methodology was developed by Baguley and Stockton (2002) within the EPSRC Grant Reference: GR/M58818/01, "IMI: IMPROVING THE COST MODEL DEVELOPMENT PROCESS (COSTMOD)", for the choice of type-1 fuzzy logic structural elements.
5. Refine choices in (1), (2), and (3) through a learning mechanism.

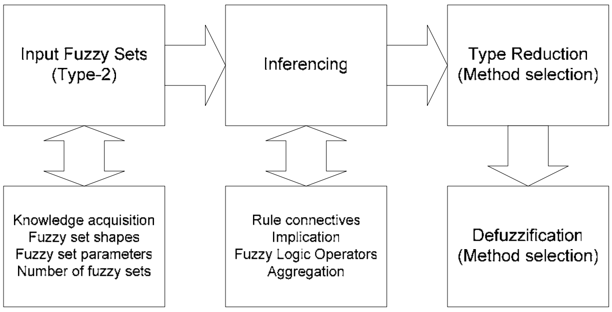

Figure 2: Sequence of steps in using fuzzy logic

9 IDENTIFY CONCEPTS IN THE MODEL

Concepts in the model include the nouns and adjectives of the problem. For example the nouns, “motor”, “lift”, “time”, “labour”, “cost”; and the adjectives “low”, “medium”, “high”, and “very”. Brain storming methods are typical for identification, for example the use of relationship diagrams, as shown in Figure 3, allows the picturing of concepts and the relationships between them using arrows. The formation of rules is made easier using such diagrams, i.e. the identification of relationships using the arrows.

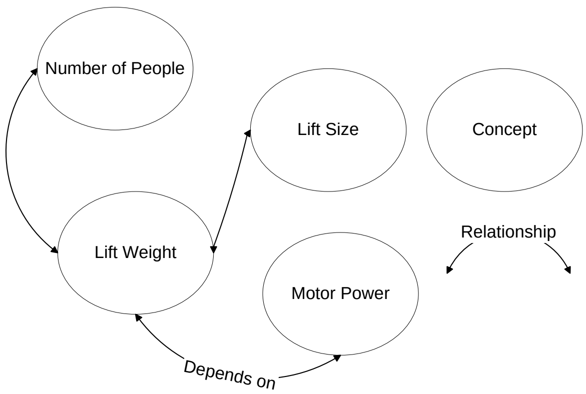

Figure 3: Relationship diagram to identify concepts for a fuzzy logic model

10 IDENTIFY EXPERT RULES

The format of expert rules (if then rules) is familiar to many. For example if “size” of “lift” is “medium” then “motor” “power” is “low”. Of importance is whether the rule base is to be a “complete” rule base or an informal and ad-hoc collection of rules the expert uses whilst informally performing trade-offs between cost and changes in MCAD and ECAD designs. A complete rule base involves every single combination of variables. Complete rule bases consume more resources to build, and when there are lots of rules, are difficult to form effectively.

11 PRODUCE TYPE-2 FUZZY SETS

Firstly the range of the variables (also known as the Universe of Discourse) with which to cover with fuzzy sets, must be identified. Subsequently the following decisions are required:

1. shape of the fuzzy sets (do not all have to be the same, for example a mixture of triangular and trapezoidal shapes)
2. parameters of the shape of the fuzzy sets (for example the width and centre point of a triangular fuzzy set)
3. overlap between fuzzy sets (for example how much fuzzy set widths coincide on the range of the individual variables)
4. “blurring” of the fuzzy sets, i.e. making the type-1 fuzzy sets into type-2 fuzzy sets (as shown in Figure 4), (for example each precise degrees of membership to a fuzzy set are made into a type-1 fuzzy set)

This sequence of tasks, here, is not a unique one. The decision can be a difficult one, but is aided by the robust properties of fuzzy logic, i.e. errors in detail of the shapes of the fuzzy sets can be accommodated by the model in that accuracy is not greatly reduced. In addition, there is the potential extra robust properties of type-2 fuzzy sets. Degrees of membership to a fuzzy set and the ideas of set theory are essential, but work has been done in which such knowledge is shielded from experts by indirect questions provided in a written questionnaire ([11]). Therefore only their domain knowledge is required.

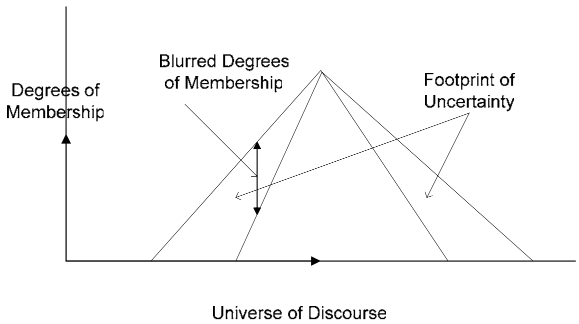

Figure 4: Type-2 fuzzy set

12 FUZZY LOGIC OPERATORS

The fuzzy logic operators are mathematical operators or rules for combining fuzzy sets for inferencing and particularly involve:

(1) connectives in rules, e.g. the “AND” operator
(2) implication operator for using rules
(3) aggregation operator for combining the results of rules

13 TYPE-REDUCTION

Type reduction involves the conversion of the type-2 fuzzy set produced after inferencing into a type-1 fuzzy set.

14 DEFUZZIFICATION

Defuzzification converts a fuzzy set into a single value. This step is most appropriate for control system applications.

15 REQUIREMENTS FOR A KNOWLEDGE ACQUISITION METHOD FOR TYPE-2 FUZZY LOGIC AND ECAD

An essential step in using fuzzy logic as proposed in this research is the knowledge acquisition phase. Experts' domain knowledge is mapped into fuzzy logic structural elements. Some of the requirements of a knowledge acquisition method are shown below.

1. To capture the terminology of ECAD and MCAD engineers
2. To consistently capture the parameters of type-2 fuzzy sets using (1)
3. To hide fuzzy logic knowledge from ECAD and MCAD experts

16 DIGITAL ENTERPRISE TECHNOLOGY (DET) ARCHITECTURE FOR THE USE OF TYPE-2 FUZZY LOGIC AND ECAD.

Due to the lack of research and practice into type-2 fuzzy sets, there are no commercial software packages available to perform type-2 operations. Mendel ([2]) at the University of California has produced "m-files" that can perform some type-2 operations, for the MATLAB fuzzy logic toolbox. The MATLAB fuzzy logic toolbox is a well known software package for performing type-1 fuzzy logic operations. The essential aspect of MATLAB is its intuitive Graphical User Interface. The GUI promotes the modelling of expert intuition. Digital Enterprise Technology (DET) is defined as: "the collection of systems and methods for the digital modelling of the global product development and realisation process in the context of life cycle management". A fuzzy logic model can depart from an integrated systems architecture, by standing outside of any collection of software components, and to be used by an expert to express his opinion (Figure 5). The expert may use existing DET components within a DET architecture to formulate this opinion, but need not connect MATLAB to any data sources, as would be the case in processing numerical data.

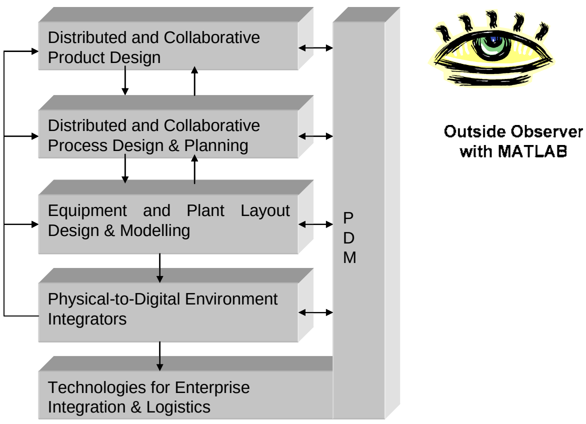

Figure 5: Observer using a DET architecture to formulate opinion

17 HOW TO USE THE TYPE-2 FUZZY LOGIC MODEL

1. Crisp values (non-fuzzy, i.e. ordinary numbers) for the input values are put into the model,
2. Because each value corresponds to a degree of membership to a type-2 fuzzy set, which is a type-1 fuzzy set, the input value corresponds to this type-1 fuzzy set,
3. This type-1 fuzzy set is combined with similar type-1 fuzzy sets produced for the other input variables, from their respective input values, as indicated by each rule in turn,
4. The resulting type-1 fuzzy set from the several combinations of input values, is combined with the type-2 fuzzy set corresponding to the output variable for each rule in turn,
5. All these resulting type-2 fuzzy sets from each rule are aggregated together to form one overall type-2 fuzzy set,
6. this type-2 fuzzy set undergoes a type-reduction operation to form a type-1 fuzzy set,
7. this final type-1 fuzzy set is defuzzified.

The structure of a type-2 Fuzzy Logic System is shown in Figure 6, It is clearly seen that there is a separate type-reduction stage, this is needed to defuzzify type-2 fuzzy sets.

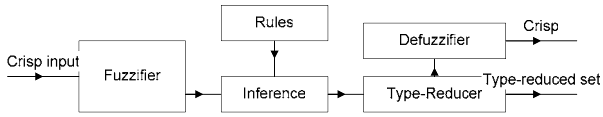

Figure 6: Type-2 fuzzy inference system

18 CONCLUSION

There is a gap in provision for modelling the design of electrical and mechanical components when they affect each other. The interaction of electrical and mechanical components, for example when predicting costs, is captured using expert rules and quantified using type-2 fuzzy logic. Type-2 fuzzy logic is used because of the exceptional level of uncertainty within an Integrated Product Team. This uncertainty is especially prevalent because of the diversity of the 2 interacting areas of ECAD and MCAD.

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