QUALITATIVE MODELS AS A SEGMENT OF NAÏVE ENGINEERING DESIGN

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Non linear and multidimensional models of an interdisciplinary nature are needed to study a broad spectrum of tasks related to design of mechanical engineering systems. Oversimplified and therefore inapplicable results are frequently obtained as the final result of model development. A human way of making decisions is not based on numbers but on common-sense reasoning. Qualitative modeling brings additional options in the modeling of complex systems. Qualitative variables are quantified using three values only – positive (increasing), zero (constant) and negative (decreasing). The classical quantitative tools cannot deal with such variables. Typical areas suitable for qualitative modeling are design related tasks with a large number of variables. A presented case study, an optimization of a solar collector, is given in details.

Keywords : *qualitative, naïve, engineering design, heuristics, multi-dimensional optimization*

1. Introduction

Designers of complicated engineering systems cannot ignore vague, inconsistent nor incomplete information simply because it does not provide data for exact quantitative engineering models (Huang et al., 2006; Dohnal et al., 2008). It is clear that vague concepts such as future cost of materials, staff qualification, environmental sustainability, future technical progress, are all difficult to measure, i.e. to be quantified by traditional numerical methods. This is a great advantage; for details see e.g. Li et al. (2010).

Companies are interested in innovative ways of conducting their businesses. The current crisis is the main driving force. As firms strive to improve their marketing advantages, many find that traditional design techniques are no longer cost effective. Some design innovations can be attributed to the growing use of up to date artificial intelligence algorithms.

Unfortunately engineers can use the majority of methods related to artificial intelligence as black boxes only. The required mathematical/logical backgrounds are too extensive and sophisticated. However the black box approach is not feasible without elementary understanding of the basic principles. Naïve engineering is an efficient tool how to learn the basic skills with minimal time investments into studies of artificial intelligence.

Modern computers are extremely powerful tools for the purpose of number manipulation. However, their contribution in solving complex problems using common sense has so far been very small (Parsons and Dohnal, 1995). A common sense based approach to decision making potentially has much to offer. Human thought is not usually based on equations and one of the most powerful tools used by human beings to solve real problems, is common sense reasoning, see e.g. Haimes et al. 1990.

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A simple example of an equation-less knowledge item, is the following heuristics:

If solar irradiation goes up then energy gain of solar collector increases.

2. Naïve engineering design methods

A great deal of experience is needed to formalise any aspect of engineering common sense. A design problem is always solved using vaguely defined concept which cannot be formalised by traditional mathematics and consequently by available software, namely Sherin (2006). The following sub problems must be solved to optimize any complex design task:

– What role does intuitive knowledge play in physics/engineering problem solving?

– How does intuitive physics/engineering knowledge change in order to play that role?

– What are the crucial experiences that can lead to the refinement of intuitive knowledge?

– Can experiences with quantitative problem solving lead to changes in commonsense physics knowledge?

Many researchers had a bold vision of the way knowledge engineering would revolutionize engineering design, and push the frontiers of technology swiftly forward, see e.g. Sherin (2006); Tan et al. (2006). There are many information systems that use e.g. fuzzy logic, neural networks, rough sets, genetic algorithm, and other techniques in approximate reasoning see e.g. Turunen (1984) and Dohnal (1992).

Hydrodynamics is a well established segment of engineering knowledge and can be therefore used as an example. Its theory contains a very large body of mathematics, mathematical physics, and scientific software devoted to the question of predicting the flow of fluids. However, these techniques all work using numerical quantification. The numerical techniques deliver extremely precise predictions of fluids flow. However, they require correspondingly precise specifications of the boundary and initial conditions (Davis, 2008).

The key design task is related to geometric reasoning. Any mechanical engineering tasks are inevitably related to space, for details see e.g. Han and Lee (2002). This is the reason why a special branch of artificial intelligence, namely space reasoning has been studied for a long time already, see e.g. Duffey and Dixon (1988). However, the applicable results are available during the last several years; see e.g. Linden et al. (2009).

3. Qualitative modeling – tutorial introduction

There are only three qualitative values

$$\text{Positive, Zero or Negative}\,. \tag{1}$$

A qualitative solution of a qualitative model is specified if all its n qualitative variables are

$$X1,\ X2, \ldots,\ Xn\,. \tag{2}$$

Examples of variables in engineering problems are pressure, flow rate, energy, efficiency, cost, weather in the location of solar power stations etc.

Important terms used in qualitative modeling are a sequence of qualitative triplets:

$$(X1, DX1, DDX1),\ (X2, DX2, DDX2), \ldots,\ (Xn, DXn, DDXn)\ , \tag{3}$$

where Xi is the i-th variable and DXi and $DDXi$ are the first qualitative and the second qualitative derivations with respect to the independent variable to t.

If $X1$ is for example profitability, then $DX1$ indicates profitability changes (i.e. growing, declining or constant), and $DDX1$ indicates what is happening to the rate of change in profitability. Precise quantitative functions are not known. What is known is that the profitability is rising, staying constant or falling at an unknown rate of change.

Similar examples can be given for engineering parameters. Variable Energy (provided by solar panels) will grow with flow rate. (Growing means positive first derivation). The growth can reach saturation (i.e. the second derivative is negative), the growth can also be linear with increasing flow rate (zero second derivative), or the growth can be exponential with increasing flow rate (positive second derivative). The role of engineer or expert is to say which relation between energy and flow rate is the most probable without describing it quantitatively.

4. Qualitative equation-less models

A typical example of a qualitative knowledge item can be formalized by a certain simple relationship between two variables, X and Y. The complete set of relations has nine different shapes when the first and the second derivatives are taken into consideration, and if both variables X and Y are positive, there are six relations. A graphical interpretation is given in Fig. 1. These graphs simply demonstrate possible triplets. Each graph notes the triplet and identification number for computer processing.

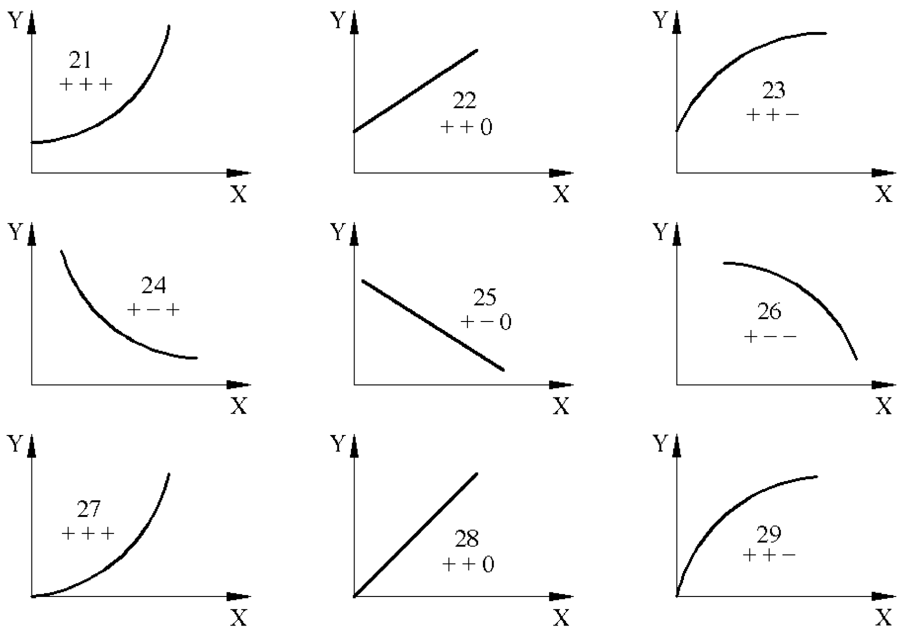

Fig.1: Triplets visualization – relation between variables X and Y meaning of first and second derivatives

All relations are qualitative. It means that nothing is quantitatively known. For example the relation 22 indicates clearly that there is a linear relationship between Y and X. If $X = 0$

then Y is positive. However, nobody can be sure of the slope, but it is clear that the slope is positive. Therefore, if expert states that energy from solar panels grow linearly with flow rate; they will use the relation 22 shown in Fig. 1.

However, there are qualitative relations which are only known vaguely so that the second derivative is unknown (unpredictable) and therefore the following description is used to help to characterize them:

If X is increasing then Y is increasing or if X is decreasing then Y is decreasing

$$M+ \,. \tag{4}$$

This relation between X and Y is known as direct proportion.

If X is decreasing then Y is increasing or if X is increasing then Y is decreasing

$$M- \,. \tag{5}$$

This relation between X and Y is known as indirect proportion.

In other words the first derivatives are related as follows:

$$DX = DY \qquad M+ \,, \tag{6}$$

$$DX = -DY \qquad M- \,. \tag{7}$$

If the expert (in the example with energy and flow rate) cannot decide for scenario 21, 22 or 23 in Fig. 1 and knows only that energy gain grows with flow rate, then he will use equation (6).

5. Case study

The following case study shows the possibility of using qualitative modeling for design/optimisation purposes. Specifically, this model deals with the design and adjustment of the flat plate solar water collector.

The following set of the variables is used:

Water flow rate (kg/s)	m
Outlet water temperature from the collector (°C)	To
Inlet water temperature to the collector (°C)	Ti
Air temperature between glazing and absorber (°C)	Ta
Collector temperature (°C)	Tc
Solar irradiance (W/m^2)	I
Absorption (–)	Al
Velocity (m/s)	v
Thickness of water level (mm)	b
Pressure (Pa)	p
Transmittance (–)	TAU
Number of glazing layers (–)	La

Take notice that some variables are not under direct control of a designer. We can give an example of Solar irradiance I, which could be influenced only by the selection of the location of the solar collector on Earth.

All chosen relations among variables are shown in Tab. 1. Tab. 1 was compiled by a team of experts, which concentrated on problems of design, simulations and testing of a flat plate solar water heating panel. The fourth column of the table shows relations between dependent and independent variables, as in Fig. 1.

Line	Dependent variable X	Independent variable Y	Type of function (Fig. 1)
1.	To	m	24
2.	Tc	m	24
3.	Ti	To	23
4.	Ta	To	23
5.	Tc	To	23
6.	Al	To	23
7.	I	To	23
8.	Ta	Ti	21
9.	Tc	Ti	21
10.	I	Ta	21
11.	Al	Ta	21
12.	Tc	I	23
13.	Tc	Ta	23
14.	To	v	24
15.	Tc	v	24
16.	Ta	v	24
17.	m	v	28
18.	To	b	23
19.	v	p	24
20.	b	p	24
21.	La	TAU	$M-$
22.	Tc	TAU	27
23.	To	TAU	27
24.	To	La	26
25.	Tc	La	26
26.	La	Ta	26

Tab.1: List of Qualitative Relations

For example, in row no. 1, it is necessary to determine the dependence between the Outlet water temperature from the collector To and Water flow rate m. When the Water flow rate is high, Velocity inside the collector is high and the heat transfer coefficient is growing. But at the same time the heating effect is reduced because the Volume of water is subjected to heating for less time. This means, the higher the Water flow rate, the lower the resultant Outlet water temperature, but it is not possible to achieve infinite temperature by means of low Water flow rate, nor zero temperature increase by high Water flow rate – this is expressed by function no. 24.

An algorithm which can be used to solve qualitative models is based on pruning of a specially generated tree of combinations. It is not the goal of this paper to describe an optimal combinatorial algorithm as it is a purely combinatorial task. For details see Vicha and Dohnal (2008).

The model given in Tab. 1 has 180 scenarios, see (3). The best possible solution for the solar panel is the situation when Outlet water temperature grows alongside growing Water flow rate. This combination provides maximum energy gain. Thereafter only scenarios which get near the required state are shown. There are 18 such scenarios, see Tab. 2.

No.	m	To	Ti	Ta	Tc	I	Al	v	b	p	TAU	La
1	+−+	+++	+++	+++	+++	+++	+++	+−+	+++	+++	+++	+−−
2	+−+	+++	+++	+++	+++	+++	+++	+−+	+++	++0	+++	+−−
3	+−+	+++	+++	+++	+++	+++	+++	+−+	+++	++−	+++	+−−
4	+−+	+++	+++	+++	+++	+++	+++	+−+	++0	+++	+++	+−−
5	+−+	+++	+++	+++	+++	+++	+++	+−+	++0	++0	+++	+−−
6	+−+	+++	+++	+++	+++	+++	+++	+−+	++0	++−	+++	+−−
7	+−+	+++	+++	+++	+++	+++	+++	+−+	++−	+++	+++	+−−
8	+−+	+++	+++	+++	+++	+++	+++	+−+	++−	++0	+++	+−−
9	+−+	+++	+++	+++	+++	+++	+++	+−+	++−	++−	+++	+−−
10	+−0	+++	+++	+++	+++	+++	+++	+−0	+++	+++	+++	+−−
11	+−0	+++	+++	+++	+++	+++	+++	+−0	++0	+++	+++	+−−
12	+−0	+++	+++	+++	+++	+++	+++	+−0	++−	+++	+++	+−−
13	+−−	+++	+++	+++	+++	+++	+++	+−−	+++	+++	+++	+−−
14	+−−	+++	+++	+++	+++	+++	+++	+−−	++0	+++	+++	+−−
15	+−−	+++	+++	+++	+++	+++	+++	+−−	++−	+++	+++	+−−
16	+−+	++0	+++	+++	+++	+++	+++	+−+	++−	+++	+++	+−−
17	+−+	++0	+++	+++	+++	+++	+++	+−+	++−	++0	+++	+−−
18	+−+	++0	+++	+++	+++	+++	+++	+−+	++−	++−	+++	+−−

Tab.2: Selected scenarios

The Tab. 2 describes individual variables in a scenario (3) as a function of time. For example the scenario number 1 shows that when variables To, Ti, Ta, Tc, I, Al, b, p and TAU are increasing. The corresponding first derivatives DX, see (3) are positive. The variables m, v and La are decreasing.

In all scenarios it is desirable to achieve the highest Temperature of outlet water from the collector, such as (+++) and (++0) and also as high as possible a Water flow rate. It stands to reason then, that these two variables are opposing each other and it is therefore not possible to achieve the highest Outlet water temperature from the collector together with the highest Water flow rate.

The scenarios mentioned above are the optimal requirements, where the main criterion is the highest possible Outlet water temperature from the collector, To. This scenario is possible to achieve with three different Water flow rates m (+−+), (+−0) and (+−−).

In this case we will consider the Thickness of water level b and Pressure p. It is obvious to choose the scenario with the lowest pressure, because high pressure brings a number of structural problems. These problems are connected with overall design solution and hence with extra production costs. Based on these above given presumptions the scenarios no. 6 and no. 14 are the only acceptable ones.

No.	m	To	Ti	Ta	Tc	I	Al	v	b	p	TAU	La
6	+−+	+++	+++	+++	+++	+++	+++	+−+	++0	++−	+++	+−−
14	+−−	+++	+++	+++	+++	+++	+++	+−−	++0	+++	+++	+−−

In these scenarios all variables except Water flow rate and Pressure are the same, which means the final decision will adhere to these two variables.

In both scenarios the Water flow rate is decreasing and Pressure is increasing in time, but the second derivations are differing. Scenario no. 6 seems to be optimal when considering To, m, b and p because the Water flow rate drop expressed by the triplet (+−+) has better tendency than the drop in scenario 14.

6. Conclusion

Naïve engineering design will reach its maturity probably soon. Its formal tools will be based on results of artificial intelligence. Methods of naïve engineering are inspired by non numerical algorithms used by engineers to tackle such tasks which cannot be solved by computers using currently available software.

Qualitative reasoning is a nucleus of those algorithms. The main advantages of the qualitative decision making are:

- No numerical values of constants and parameters are needed.
- The set of solutions (optimization scenarios) is provably complete i.e. there cannot be any other qualitative behaviors that are not generated by the qualitative model.
- Qualitative (vector) optimization can be done separately from the actual qualitative simulation.

Further development of naïve engineering is urgently required. Different versions of qualitative synthesis is a very promising next development step, see e.g. Popela et al. (1992, 1993).

The described method when used in engineering application is in its early stages, but today it is already possible to see real outcomes, which can have a huge impact on the construction of complex engineering structures. It's possible that in the future, thanks to this method, it will be possible to introduce a pre-set of complex systems with so many income variables that nothing conventional can compare. The method is in its infancy; therefore it is possible to expect rapid development and the consequent application for use in many fields from engineering to the economy. It is possible that the system can be developed to be operationally successful with respect to costs.

This simple example of design and control of energy-hydro-mechanical system was chosen in order to demonstrate the method of qualitative modeling. The method is only launching in the area of engineering mechanics. This type of modeling provides a tool for designers of very complicated hydraulic systems, chemical units and complex systems such as nuclear power stations.

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