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Systematic Search for Design Contradictions in Systems' Architecture: Toward a Computer Aided Analysis

Eric Coatanéa[a*], Sarayut Nonsiri[a], Ricardo Roca[b], Faisal Mokammel[a], Juliane Kruck[c] and François Christophe[d]

[a] *Department of Mechanical Engineering and Integrated Systems, Tampere University of Technology, Tampere, Dynavio Cooperative, Espoo, Finland and Aalto University, Espoo, Finland*
[b] *The Johns Hopkins University Applied Physics Laboratory.*
[c] *Karlsruhe University, Karlsruhe, Germany*
[d] *Department of Computing Science, Tampere University of Technology, Tampere, Finland*

Abstract Time pressure imposed to the engineering design process is one fundamental constraint pushing engineers to rush into known solutions, to avoid analysing properly the environment of a design problem, to avoid modelling design problems and to take decision based on isolated evidences. Early phases in particular have to be kept short despite the large impact of decisions taken at this stage. Significant efforts are currently spent within different engineering communities to develop a model-based design approach adapted to conceptual stages. Developing such type of models is also challenging due to the fuzziness of the information and due to the complexity of the concepts and processes manipulated at this stage. Currently few support tools are really capable of really supporting an analysis of the early design concepts and architectures. Simultaneously the approach should be fast, easy to use and should provide a real added-value to efficiently support the decision and the design process. The present article is presenting a framework based on a progressive transformation of the design concepts. The final material generated by this transformation process is an oriented graph with different types of classified variables. This graph can be processed as described in the article to automatically exhibit the conflicts or contradictions present in the design concept architecture. The article is proposing two main contributions which are a real move toward model development at conceptual stage and the possibility to process those models to detect solution weaknesses. The discussion is presenting further developments and possibilities associated with this method.

Keywords: Conceptual design, model-based design, conflicts, contradictions, TRIZ, graph theory, dimensional analysis, qualitative physics

1. Introduction

The present research work is part of an ambitious project aiming at developing a computer aided approach for early design support and modelling. In this article the authors present a systematic approach to detect design conflicts in early solutions architectures. The concept of contradictions in this research area can be also called "conflicts" (Yan and Zeng, 2011). How to discover systematically and automatically the contradictions are usually not extensively discussed in engineering and TRIZ literature (has described, 1984)

* Corresponding author. Email: eric.coatanea@tut.fi

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(Savransky, 2001). The authors did not find in this literature a precise definition and a systematic approach for highlighting the physical contradictions. The contradictions are found more using expert knowledge. A contradictions in this research work is defined as a conflict between competitive objectives that system architecture should fulfil simultaneously.

Being able to systematically highlight design contradictions is a real challenge when systems are becoming complex and when an overall understanding of the system behaviours and interactions is difficult to grasp. Nevertheless, the potential benefits of systematically extracting contradictions in existing systems designs are potentially very important. This would in particular provide a powerful approach to systematically analyse the potential value of possible design strategies. This provides and help for systematically analysing solutions will support the development of innovative solutions in the case of new product development or in the case of incremental innovations.

The present article is organized in the following manner. At first, in section 2, a brief state of the art related to the concept of contradictions is developed in order to present some general principles associated with human cognition that are embedded in the concept of contradiction. Then, in section 3, the causal ordering methodology used by the expert group to generate the causal graph of the air bearing used in this article is introduced. The future software development works related to the semi-automatic causal ordering are also mentioned. In section 4, the clustering process of the variables is described as well as the qualitative definition of the objectives. In section 5, the mathematic machinery used to generate laws between influencing and influenced nodes is described. In section 6, the mechanism used to propagate the elementary objectives inside the network is presented. The sections 5 and 6 are forming the core of the contributions presented in this work. In section 7, the results are presented. The results are presenting the software tool resulting from the theory presented in the sections 5 and 6 of this article. The validation procedure is also described.

In section 8, the discussion part is analysing the contribution of this work and the future developments of the approach. The openings toward search for different design strategies that can be extracted from this analysis is made.

2. Background

2.1. System 1 and system 2 and the link with our work

In his topical book related to brain behavioural analysis Daniel Kahneman (Kahneman, 2011) presented an approach analysis our behaviour from a double mode point of view. He named those modes system 1 and system 2. System 1 is the automatic and fast thinking mode. System 2 is the analytical and slow mode. Different human activities, especially when they are involving time pressure, risk of wrong decisions and strong impact of decisions have to be supported to allow the slow and reflective mode of our brain, better to be used in those situations, to be activated.

Early engineering development activities (including requirement engineering, initial concepts developments and strategic decisions regarding the concepts to be developed) belong to this class of activities. A new form of tool has to be imagined for supporting the use of the analytical and slow mode.
This support should build causal relationship when possible because the human cognition is naturally classifying the events in form of causal relationships. Other constraints related to the early design activities are the fuzziness of the information and the use of natural language. For these reasons scientific approaches usually located outside the borders of engineering design have to be considered to develop such type of analysis approach.

2.2. Dialectical thinking and contradictions

Peng and Nisbett (Peng & Nisbett, 1999) demonstrated that there are four possible psychological responses to contradictions. First response is not to deal with contradiction at all, or to pretend that there is no contradiction. Second response is to distrust both pieces of information. Third response involves

comparing both items of information, then deciding that one is right and the other is wrong. Fourth response is to retain basic elements of the two opposing perspectives and believe that both perspectives might contain some truth, even at the risk of tolerating a contradiction. Such an approach would not regard two contradictory propositions as a contradiction, but would rather attempt reconciliation, with the result that both are believed to be true. This cognitive tendency toward acceptance of contradiction could be defined as dialectical thinking. Nakamura (Nakamura, 1964; Nakamura, 1985) believe that this dialectal thinking is present in the Asiatic cultures, the world is viewed in constant flux and the parts of this word cannot be understood except in relation to the whole. On the contrary, in Western cultures (Cromer, 1993), contradictory propositions are unacceptable by the laws of formal logic part of the tradition since Aristotle, and respond to propositions that have the appearance of contradiction by differentiation; deciding which of two propositions is correct.

Nevertheless, there is a long tradition of dialectical reasoning in western philosophy too. Marxist dialectical thought emphasized the permanence of opposition and contradiction in the real material world, and therefore in thought about reality.

A dialectic process can also be described in science. Indeed, according to Kuhn (Kuhn, 1970), creative scientific activities including design activities are dominated by constant manipulations of contradictions. In his analysis of the work of Kuhn, Basseches (Basseches, 2005) gives the following explanation of the Kuhn's dialectical analysis of the history of science: "Within a scientific discipline, research is shaped by what he called a paradigm. A paradigm binds together implicit assumptions about the phenomena being studied with assumptions about the methodology appropriate for studying those phenomena and with methods of defining problems and recognizing solutions. According to Kuhn, research following a paradigm tends to produce anomalies (i.e. findings that are not easily reconciled with other knowledge in the field). When enough anomalies are produced to make scientists within the field uncomfortable, new alternative paradigms are advanced that compete with the dominant paradigm. A scientific revolution has occurred when a new more comprehensive paradigm become dominant to define the nature of the field."

The dialectical thinking process applied to the Engineering Design implies understanding the design problem, and locating the contradictions.

In contrast with other methods of solving problems, TRIZ emphasizes the contradictions and recommends solving them instead of making the usual engineering trade-offs (Altshuller, 1984). TRIZ is especially interesting because an analysis of contradictions types and problems nature have been analysed in the TRIZ literature. Savransky in his introduction to TRIZ methodology (Savransky, 2001) distinguished different types of contradictions and structure of problems that are worth mentioning in this article. Altshuller (Altshuller, 1984) and Savransky (Savransky, 2001) distinguished three types of contradictions: administrative, technical and physical contradictions. This terminology is not perfect as we will notice it in the course of this paper, however the terminology is widely used in the TRIZ community and it is probably better for conciseness reasons to keep it in this article.

Administrative contradictions: This is something required to make, to receive some result, to avoid the undesirable phenomenon, but it is not known how to achieve the result.

Technical contradictions: An action is simultaneously useful and harmful or it causes Useful Function(s) and Harmful Function(s).

Physical contradictions: The physical contradiction implies inconsistent requirements to a physical condition of the same element of a Technical System (TS) or operation of a Technological Process (TP). For example, we want that an insulator in semiconductor chips has low dielectric constant k in order to reduce parasitic capacities and we want that insulator in semiconductor chips has high dielectric constant k in order to store information better.

The physical contradictions as well as the technical contradictions are usually crystallized during the problem analysis. Sometimes the technical contradictions can be obtained by analyzing techniques in the framework of Root Cause Analysis or Goldratt's Theory of Constraints (Goldratt, 1998).

The distinction between three types of contradiction in the TRIZ approach should be seen as three levels of understanding of the contradictions and problem statement.

The administrative contradiction is vague, is temporary, has no heuristic value and does not show a direction to the answer.

Administrative contradictions: It is necessary to obtain some results but at the same time avoiding some other effects potentially causally associated.

The technical contradiction can be stated using two IF BUT conditions with an exclusive OR conditions (XOR) in between. XOR is used to avoid the ambiguous condition when both conditions are true. Exclusive or excludes that case. This is sometimes presented as "one or the other but not both".

Technical contradictions: If the Useful action happens then one objective is attained but a harmful action is degrading another objective.

The physical contradiction is presenting the finest level of refinement of the problem formulation. A given subsystem should have the property A to execute a necessary function (defined before in the two previous refinements stages) and a property non A or anti-A to satisfy the conditions of the problem.

Physical contradictions: The physical contradiction implies inconsistent requirements to a physical condition of the same element of a Technical System (TS) or operation of a Technological Process (TP).

2.3. Causal graph and contradictions viewpoints for supporting cognitive activities related to early design

The two first sections have developed the initial idea that there is a need to support slow and deep analysis in early engineering design phases. The first hypothesis in this research work is that a new form of computer tool has to be created to support the slow and analytical early analysis process in design. The method proposed in this work to this hypothesis is to use causal graph approaches because they are well adapted to human way of functioning (Kahnelman, 2011). For this reason we will develop a causal graph approach in this work to support the use of the system 2.

Second, it has been proposed that dialectic thinking in engineering using contradictions can be considered because it is a powerful way to overcome limitations of existing solutions.

The present article is then trying to take benefit of those two combined approaches (i.e. casual graph representation and contradictions analysis) to propose a new form of computer support tool that can be used to support the early design stages.

The following sections are developing those two central ideas and a computer support method is introduced.

3. Causal Ordering Methodology

Graphs are widely used to represent and model different aspects of the world. They are used in almost all the domains where representation and modelling are required. A graph is a visual representation formed of nodes and vertices. The nodes (or vertices) and edges represent many different elements such as networks of communication, data organization, devices, flows, etc.

The edges can be directed or not directed. If the edge is directed, a causality relation is defined. For example, the architecture of a system can be represented by a directed graph. The vertices are the components and sub-systems of the system and directed edges from sub-system A to sub-system B represent the causality of the flows linking A to B. For example if A is a computer and B the wings of a plane, the edges are representing the flows between those sub-systems such as hydraulic fluid or electricity for example. This representation is very general.

In directed graph, causal relations are established between nodes. In an engineering context, the nodes can represent different viewpoints of a system to design or of a designed system such as the requirements, functions or system's interactions variables. In this article, a graph is used to represent a certain aspect of the topology of a physical object or system. The nodes are representing the most precise level of granularity which is the representation of the causal interactions between variables.

The variables are used to represent and to model the behaviour of engineered systems.

Different methods can be used to process the graphs. The goal is to extract from graphs valuable information or analysis not directly visible. In order to analyse graphs, two elements are required; a computer and a method to represent a graph in a computer system. There are mainly two different ways of coding graphs in a computer system. Theoretically one can distinguish between list and matrix structures. Matrix representation of a graph is a powerful and general representation approach allowing the application of the entire spectrum of methods coming from the branch of mathematics named linear algebra. The present article is directly employing different approaches derived from linear algebra to extract different levels of information such as coupling and correlations structures described in Newman (Newman, 2010).

Before processing a graph, there is a need to establish a causal graph linking the different variables used to represent a system. This is requiring first to establish a list of the meaningful variables required to represent properly the phenomena to be analysed. Second, a classification of the variables has to be determined in order to facilitate the search for causal interactions between variables.

The concrete example of an air bearing is used in this article to exemplify the approach developed by the authors for facilitating the creation of this type of causal graph.

3.1. The air bearing component used to exemplify the causal ordering method

An air bearing is a mechanical component that can achieve virtually frictionless motion. Due to that characteristic, air bearings are commonly used in 3D coordinate measurement machines and other machines requiring high precision positioning capabilities. Air bearings are usually aerostatic bearings that utilize an external air supply to create the air film between the two surfaces. Because contact is avoided, the bearing surfaces will not wear. The bearing surfaces are normally high quality machined surfaces, and the air gap between the surfaces are of the order of 5 µm to 10 µm.

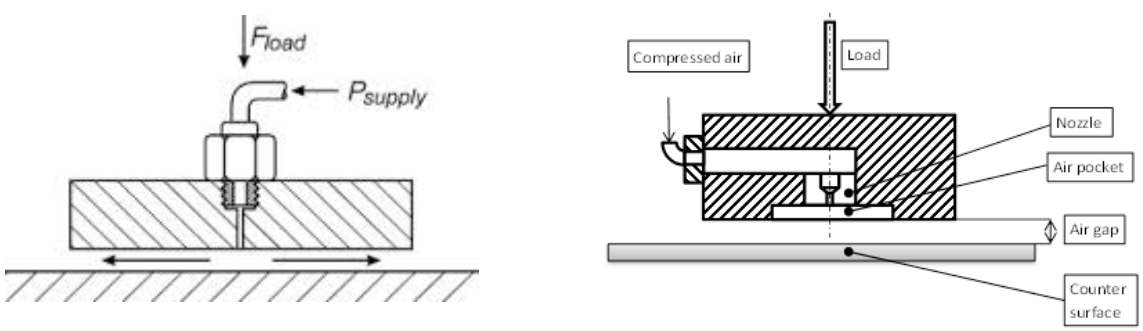

Fig. 1 Structure of an air bearing.

A simple aerostatic bearing for flat surfaces consists of a body featuring a small-diameter nozzle connected to the air supply and providing the air flow to the gap between the bearing and its counter surface (see Fig 1). Higher load capacity can be achieved if the nozzle is connected to an air pocket. The load carrying capacity of the bearing is determined by the area of the bearing surface and the pressure distribution between the surfaces.

The following part of the article is describing the step by step methodology used with the air bearing specialists to generate the causal ordering graph. The approach itself is derived from the research work of Coatanéa (Coatanéa, 2005; Medyna, *et al.*, 2012).

3.2. Selection of the system boundaries and systematic listing of the meaningful system variables

In the present study, we start defining the boundaries of the study. The boundaries include the air bearing and its counter surface but not the air production system. The rational for this decision is the focus given to the air bearing air consumption improvement. It can be argued that these limited boundaries are restricting the potential for radical innovation associated with the general functionalities of an air bearing which are to carry loads and to move loads. The authors of this article also agree with this potential critic. Nevertheless the central idea in this work is to use the air bearing case as an exemplification case. The simplicity of the case is then fundamental in this context to understand the global graph based approach core of the article.

Having defined the boundaries of the analysis, it is necessary to define the fundamental set of variables used to describe the problem. The authors propose to use a taxonomy pattern adapted from Hirtz et al. (Hirtz *et al.*, 2002) and augmented by Coatanéa (Coatanéa, 2005). The taxonomy is organized along a set of generic categories of variables encompassing all the variables and their measuring units required to describe later the system behaviour and search for the contradictions. The taxonomy is organized around four categories listed below.

(1). The domain, the energies and the fields related to the study,
(2). The power variables (efforts and flows),
(3). The state variables (Displacements and momentums),
(4). And the connecting variables.

The three first categories presented in this article are present in the initial taxonomy developed by Hirtz and her colleagues in NIST (Hirtz *et al.*, 2002). The two elements added by Coatanéa (Coatanéa, 2005) are the last category, the connecting variables and the organization of those variables inside a functional arrangement.

Indeed, those variables can be clustered in categories representing the internal structure of the functional boxes (e.g. state and connecting variables) and the links between those boxes (e.g. the power variables). Those links are the inputs and outputs of the boxes in Fig 2. The designed systems are themselves implemented in a certain domain of physics (i.e. Mechanic) using certain types of engineering energies (i.e. hydraulic) and within a certain field (i.e. translational movement).

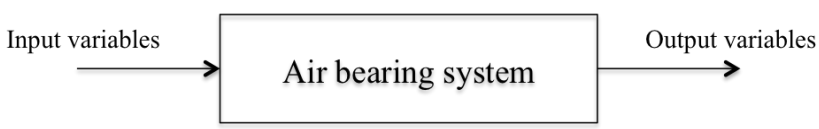

Fig. 2. White box model (INCOSE, 2010) of the air bearing.

The physical laws used to associate those variables and describing the complex interactions are not included in this taxonomy. The research team which has authored this article has developed a software tool to generate automatically a causal ordering which do not require the direct knowledge of those variables. The automatic causal ordering is not presented in this article. This automatic approach as such has not been used in the present example to generate the causal ordering but has been verified using the example of the air bearing.

The usage of a classification is providing an elementary structuration of the variables representing a basic level of architectural representation for a system.

In this taxonomy, the connecting variables deserve specific emphasize because they are not part of the initial taxonomy of Hirtz et al. (Hirz *et al.*, 2002) but nevertheless fundamental to understand the behaviour of a system. They connect effort, flow, displacement and momentum into physical equations. The connecting variables are for example the dimensions of the air bearing as well as the properties of the fluid to be used. This category of variables is used to describe the topology, the material properties. The following figure (see Fig. 3) summarizes the key variables describing the topology of the air bearing and belonging to the category of connecting variables.

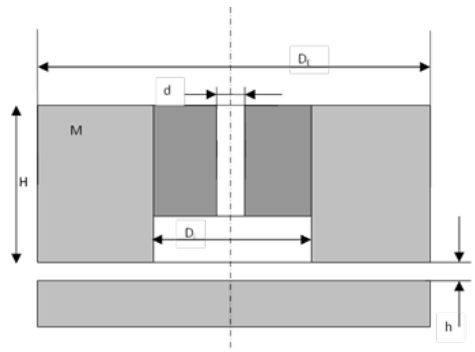

Fig. 3. Key connecting variables associated with the geometry of the air bearing.

All the categories of variables in the taxonomy used in this work are associated with their SI units represented in form of the combination of their base units (i.e. Mass, Length and Time for the example of the air bearing). The variables and base quantities are listed in the table below.

Table 1. List of variables and combination of base variable (units) used to measure them ([x] represents the combination of base variables for the variable x)

Input variables (set of power variables and connecting variables)	System variables (set of state and connecting variables)	Output variables (set of power variables and connecting variables)
Input pressure $[P] = M.L^{-1}.T^{-2}$	$Gap[h] = L$	Output pressure $[P_c] = M.L^{-1}.T^{-2}$
External force $[F] = M.L.T^{-2}$	Injection diameter $[d] = L$	Force to counter act $[F_c] = M.L.T^{-2}$
Input air flow $[f_A] = L^3.T^{-1}$	External diameter of the bearing $[D_E] = L$	Output air flow $[f_0] = L^3.T^{-1}$
Atmospheric pressure $[P_{adm}] = M.L^{-1}.T^{-2}$	Internal chamber diameter $[D_I] = L$	
Acceleration of gravity $[g] = L.T^{-2}$	Mass of the chamber $[m] = M$	
Mass density $[p] = M.L^{-3}$	Roughness of the counter surface $[R_a] = L$	
Velocity of the chamber $[V_c] = L.T^{-1}$	Air bearing stiffness $[K] = M.T^{-2}$	

3.3. Graph representation of the cause-effect relations

In Table 1, an elementary causal ordering is already emerging. This causal ordering is present also in Fig. 2 and shows that a causal propagation is flowing from the input variables, to the system variables up to the output variables. Nevertheless, another heuristic rules are required to develop further the finest structure of a causal graph.

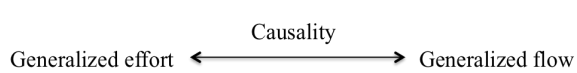

Fig. 4. Heuristic rule 1, double causality between generalized effort and generalized flow.

First, it can be noticed that inside the set of the power variables, a double causal links exists between effort and flows. For example in the case of the pneumatic energy used for the air bearing; an increase of

the *Input pressure* injected in the air bearing is instantly provoking an increase of the *Input air flow* too. Symmetrically an increase of the *Input air flow* is also generating instantly an increase of the *Input pressure*. This rule can be generalized to all the associated *generalized efforts* and *generalized flows* (see Fig. 4).

The first heuristic rule is imposing causal links inside clusters of the input and output variables. Second in all laws from any domains (physics, economics, etc.), the principle of dimensional homogeneity has to be verified (except for the links between generalized efforts and flows). The dimensional homogeneity rule can be applied to the links existing inside columns in Table 1 but also to links between columns. Causal links between columns applies when behavioural laws are taking place. The output base units being a combination of the input base units and system variables base units (see Fig. 2). The dimensional homogeneity should apply to each single node of a causal graph.

The Table 1 has been used to guide the group of experts in the causal graph construction by asking them to answer to three following questions.

(1). What are the causal relations existing between elements of each column taken separately?

(2). What are the causal relations existing between columns (look in particular for relations between Inputs and system variables as well as System and Output variables)?

(3). Can you verify that the dimensional homogeneity is verified for each of the nodes having incoming edge (the rule does not apply for links between effort and flow variables)?

The graph provided in Fig. 5 is showing the result of the causal ordering process supported by the elementary heuristics rules and the questioning process above. The black edges are associated with the use of heuristic rule 1 (e.g. double causality between generalized efforts and flows in similar columns) and question 1. The blue edges are associated with the use of heuristic rule 2 and of the questions 2 and 3.

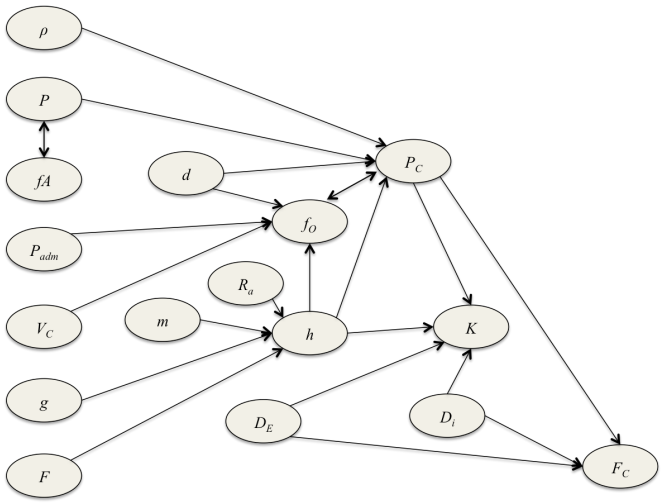

Fig. 5. Cause-effect relations between variable for the air bearing without the classifications of variables into categories.

4. Clustering Process of the Variables and Discovery of the Performance Variables

The central objective in this section is to transform the causally ordered graph of Fig. 5 into a tool for analysing the qualities and weaknesses of system architecture.

Designers during the evaluation phases of solutions want to analyse the different performance aspects of a solution. They also want to analyse more specifically the architecture of the solutions by evaluating the impact of other variables on the performances. Accessing the level of controllability of different variables influencing the performances helps evaluating the general level of flexibility of the design solutions. Finally, searching for existing contradictions in the current system architectures can provide insight toward development of better solutions.

The claim of the authors is that graph analysis can support these different design objectives. A graph analysis can be done by analysing specific areas of graphs or by analysing generic properties in the graphs structure. The analysis can be static or dynamic. To extract from a graph the specific zones of interest for designers, there is a need to highlight the main categories of variables existing in a system. In literature different classifications of the system variables are existing in work related to bond graph (Shim, 2002), classifications (Hirtz *et al.*, 2002), early design stages (Coatanéa, 2005).

In these references, different categories of variables can be distinguished. First the exogenous variables, the variables that are imposed to designers and that cannot be controlled within the current boundaries of the studied system. The exogenous variables are of the type *power* variables or *connecting* variables and are not influenced by other variables (within the selected boundaries). They are consequently located in the left column of the Table 1.

Second the design variables, which can be directly or indirectly adjusted and controlled by designers. They are providing design freedom to the designer because they help influencing and controlling other variables. Some design variables are easier to control because they are not influenced by any other variables. A second sub-category is harder to control because of the multiple influences coming from other variables. The design variables are characterized by their belonging to the categories *state* or *connecting* variables defined in the middle column of Table 1. The design variables are part of the system architecture. They are located in the system's column of the Table 1. In addition, the design variables nodes in a graph can be recognized because they have more outgoing edges than incoming edges.

The third category is formed by the performance variables. The performance variables are present in different variable categories, the *power*, *connecting* and *state* variables. Discovering the performance variables in system architecture can difficult. Nevertheless, several patterns are always present to characterize the performance variables. The performance variables are usually located at the end of a chain of interactions with other variables. They can also be formed by dimensionless ratio of power variables for example but even the ratio are involving output variables or variables located at the end of the chain of interactions.

For the three categories of variables presented above it is useful from a design support point of view to automate the classification of the variables into the three categories of variables described above (i.e. exogenous, design and performance variables). This can be done by combining the knowledge extracted from those categories of variables as presented above and the system architecture, but also by taking benefit of directed graph properties. The authors have taken benefit of network analysis approaches (Newman, 2010) to extract knowledge from the directed graphs representing the system architectures. In order to select the tools that might be useful in the collection of network analysis tools, it is in particular interesting to notice that each category of the three variables categories presented above has a kind of fingerprint characterized by the amount of incoming and outcoming edges to a node. A node is representing in our selected representation a variable or a group of variables. This elementary principle can be expended by using metrics from graph or network theory (Newman, 2010) such as *node degree*, *node incoming degree*, *node out coming degree*.

The idea to use the degree of nodes (i.e. the *Incoming* and *Out coming* edges of nodes (Godet *et al.*, 2006; Newman, 2010) as a clustering metric for the system variables is exploited in this work in addition of the differentiation rules for the system variables presented above.

The Fig. 6 is presenting the different categories of variables extracted from this analysis process. This analysis is forming the basis for the contradiction analysis method described in the next section.

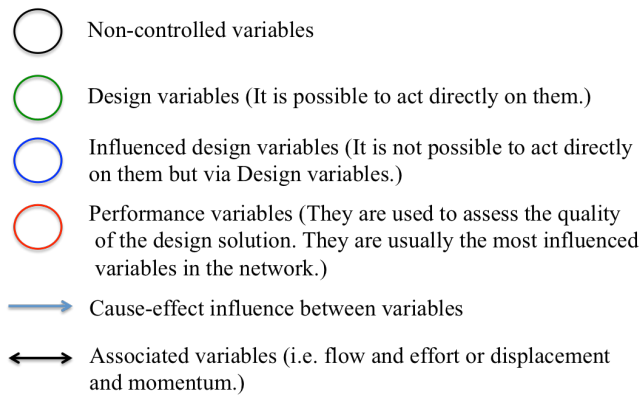

Fig. 6. Different type of variables classified by level of control.

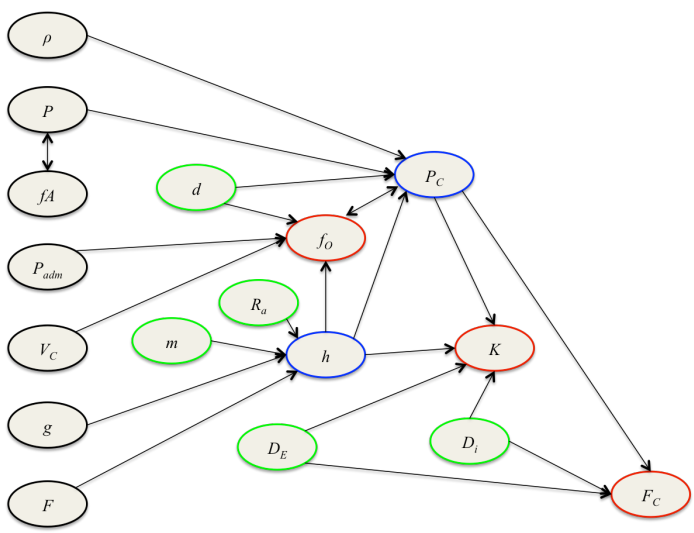

Fig. 7. Cause-effect relations between variable for the air bearing integrating the classification into different set of variables.

5. Graph Validation Contradiction Search Method

The completeness and validity of the graph in Fig. 7 depends on the initial set of variables selected as well as on the completeness of the cause-effect relationships between variables. A simple tool such as the dimensional analysis approach can be used in the case of the graph to validate the dimensional homogeneity of the graph. The method consists of analysing each of the nodes of the graph pointed out by arrows using the following approach described below and integrating research works presented by (Matz, 1959; Barenblatt, 1979; Sonin, 2001).

Let $y = \sum_i a_i x_i$ be a law. Then all $a_i x_i$ must have the same dimensions as y. If a_i are dimensionless constants, then x_i must have the same dimension than y. This is the principle of dimensional homogeneity. If the system of fundamental quantities needed in the law is in the form of 3 basic quantities namely the length L, the mass M and the time T and if the dimension $[y]$ of the variables is a combination of the 3 basic dimensions then $[y]$ has the form:

$$[y] = C_1 . L^{\alpha_1} M^{\alpha_2} T^{\alpha_3} \quad (1)$$

This form is called the product theorem in which the constant C_1 and the exponents $\alpha 1$, $\alpha 2$, and $\alpha 3$ are dimensionless numbers. When the dimensional validity of the graph has been verified, the next step consists of defining the objectives that are targeted on the performance variables. Traditionally three types of objectives are targeted. A performance variable can be maximized, minimized or a target value is expected. Using the exact same basic principle described above, it is possible to infer the impact of those performance variables on the other categories of variables implied in the graph. The method used to implement this simple idea is described in the following part of this article.

It follows from the product theorem described in equation 1, that every law which takes the form $y_0 = f(x_1, x_2, ..., x_n)$ can take the alternative form as shown in equation 2.

$$\Pi_0 = f(\Pi_1, \Pi_2, ..., \Pi_n) \quad (2)$$

Π_i are dimensionless products. This alternative form is the final result of the dimensional analysis and is the consequence of the *Vashy-Buckingham theorem*. A dimensionless number is then a product which takes the following form:

$$\Pi_i = y_i . (x_1^{\alpha_{i1}} x_2^{\alpha_{i2}} x_3^{\alpha_{i3}}) \quad (3)$$

where $\{x_1, x_2, x_3\}$ are called the influencing variables, $\{y_1, y_2, y_3\}$ are called the influenced variables in our work and $\{\alpha_{ij} | 1 \le i \le n - r, x_2, x_3\}$ are the exponents. The denomination influenced variables has replaced the denomination performance variables used initially by several authors such as Bashkar and Nigam (Bashkar & Nigam, 1990).

This choice made by the authors of this article reflects better the graph considerations included in this work. The graph representation associated with Equation 3 is presented now below in Fig. 8. In order to fulfil the basic laws of physics, the dimensional homogeneity should be valid for each node y of the generated graph otherwise a problem of dimensional homogeneity exists. It can mainly be the sign of two potential problems; a variable might have been forgotten or a causal link is missing or wrong. This can be used to assess some quality criteria of the graph presented in Fig. 8.

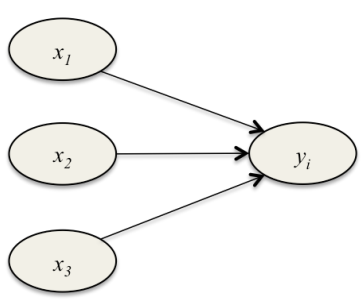

Fig. 8. Representation of the Vashy-Buckingham theorem.

After verifying the dimensional homogeneity, the next step of the computational approach consists of computing the coefficients of the dimensionless numbers presented in the last column of Table 2. To do so, basic results from linear algebra are applied. The Cramer's method is used to compute those coefficients.

Table 2. Table of influencing variables and dimensionless numbers extracted from Fig. 7

Case Air bearing		
Influenced nodes	**Initial set of influencing variables based on Figures 7 and 8**	**Associated dimensionless numbers**
h(Gap)	m, R_a, g, F	$\pi_h = h.m^a.R_a{}^b.g^c.F^d$
Pc(Pressure between the counter surface and air bearing)	P, d, h, ρ, fo	$\pi_{Pc} = Pc.P^{a1}.d^{b1}.h^{c1}.\rho^{d1}.fo^{e1}$
K(Bearing Stiffness)	D_E, D_I, h, Pc	$\pi_K = K.D_E{}^{a2}.D_I{}^{b2}.h^{c2}.Pc^{d2}$
fo(Flow of air leaving the air bearing)	d, P_{adm}, Pc, h, Vc	$\pi_{fo} = fo.d^{a3}.P_{adm}{}^{b3}.P^{c3}.h^{d3}.Vc^{e3}$
Fc(Lifting Force)	Pc, D_I, D_E	$\pi_{Fc} = Fc.Pc^{a4}.D_I{}^{b4}.D_E{}^{c4}$

Cramer's rule imposes two conditions to be able to compute the coefficients. First, the determinant of the system of equation to solve for each dimensionless number should by different from 0. Second, in order to compute a determinant, the manipulated matrixes should be a square matrix. In order to concretely exemplify the approach, the first dimensionless number related to the air bearing example is used. From this dimensionless number, $\Pi_h = h \cdot m^a, R_a^b, g^c, F^d$, a matrix representation can be developed having the form presented in Table 3.

Table 3. Matrix representation of the dimensionless number Π_h

Π_h		Influenced variables [B]	Influencing variables [A]			
		h	m	R_a	g	F
Base dimensions	L	1	0	1	1	1
	T	0	0	0	-2	-2
	M	0	1	0	0	1

The Table 3 is representing the dimensions of the variables involved in the dimensionless number π_h. The dimensions of the variables are derived from the dimensions introduced in Table1. Table 2 is also used for representing the set of variables involved in the dimensionless number. The goal of such type of table is to compute the exponents of the dimensionless numbers using the Cramer approach. The same computations principles are repeated for all the dimensionless introduced in Table 2.

The matrix A, introduced in Table 3, formed by the influencing variables is not squared. In order to be able to apply Cramer's method, variables should be combined to form a 3x3 matrix. The combination principles should simply avoid having columns which are multiple of others and columns or lines containing only 0. The new matrix *A* generated from this combination of variables is presented in Table 4. It should be noted by the readers that it is not the only possible combination. A heuristic to develop the combinations is presented later in this article.

Table 4. Square Matrix [*A*]

Π_h		Influenced variables [B]	Influencing variables [A]		
		h	$m \cdot R_a$	g	F
Base dimensions	L	1	1	1	1
	T	0	0	-2	-2
	M	0	1	0	1

The approach used after that stage to compute the coefficients, is the traditional Cramer's method yielding the following approximated coefficients in the case of Table 4.

$\Pi_h = h \cdot m^{-1} \cdot R_a^{-1} \cdot g^{-1} \cdot F^1$, the coefficients demonstrate the dimensional homogeneity of the network of variables influencing h in Fig. 7. It is not a complete proof of the validity of the model but it helps according to the authors detecting potential missing variables or completely irrelevant variables added to models. This aspect is studied more deeply below.

The usage of the clustering approach requires some guidelines to group the variables (i.e. like in the case of Table 4). An important first heuristic rule is proposed at this stage:

(1). It is advised to create clusters of grouped variables which are dimensionally rich (i.e. minimizing the number of 0 in the matrix [A] and combining variables of different types instead of variables measured using similar units).

The other important heuristic rule to apply when grouping variables is the following:

(2). Group variables that are activated at the same time in the behaviour of the studied system.

The description of the air bearing behaviour can exemplify the rule. A pressure P is introduced in the air bearing through the canal of diameter d. This is leading to a pressure Pc. This pressure Pc is acting simultaneously on the air bearing surface of diameters D_I and D_E creating a lifting force F_c, this lifting force F_c, if superior to F is generating a gap h. An output flow of compressed air f_o escapes through this gap diminishing the pressure P_c and the lifting force F_c which then diminishes h and the output flow of air f_o.

The timeline in Fig. 9 summarizes this description. Using the information provided by Fig. 9, one will notice that two clusters of variables are appearing (P, d) and (Pc, D_E, D_I). These two clusters influence P_c and K, respectively, in Fig. 7. This means concretely that the dimensionless groups used to describe the variables influencing P_c and K, respectively should be formed of this cluster when using Cramer's method.

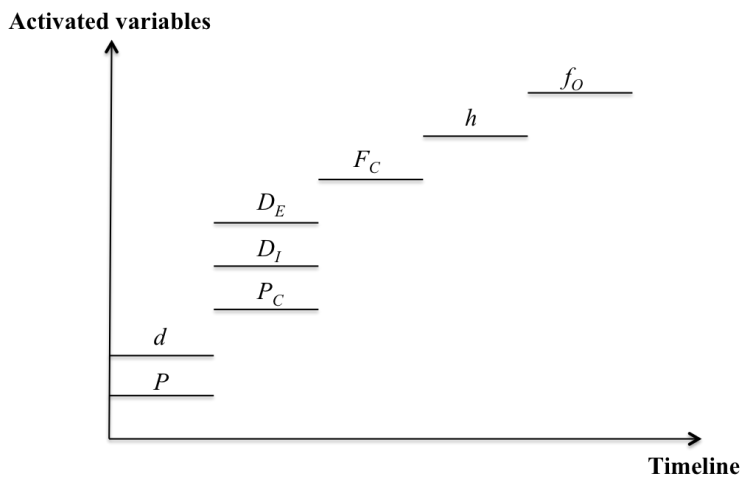

Fig. 9. Timeline summarizing the activation of the major variables describing the behaviour of the air bearing.

In the graph generated by the experts group in Fig. 7, the output pressure P_c is a hub influenced by several variables but in turn also influencing several variables. The Table 5 is, like the Table 3, derived from Table 1 and Table 2. The Table 5 is presenting the different variables associated with P_c.

Table 5. Initial matrix for $\Pi_{P_C} = P_C \cdot P^{a1} \cdot d^{b1} \cdot h^{c1} \cdot f_o^{d1} \cdot \rho^{e1}$

Π_{P_C}		Influenced variables [B]	Influencing variables [A]				
		P_C	P	d	h	f_o	ρ
Base dimensions	L	-1	-1	1	1	3	-3
	T	-2	-2	0	0	-1	0
	M	1	1	0	0	0	1

The Table 6 below is presenting a clustering approach which is not following the two clustering principles proposed above to compute P_c.

Table 6. Clustered matrix not following the heuristic principle

Π_{P_C}		Influenced variables [B]	Influencing variables [A]		
		P_C	P	$d.h$	$f_o.\rho$
Base dimensions	L	-1	-1	2	0
	T	-2	-2	0	-1
	M	1	1	0	1

The "wrong" clustering of Table 6 is generating the dimensionless number: $\Pi_{P_C} = P_C \cdot P^1 \cdot d^0 \cdot h^0 \cdot f_o^0 \cdot \rho^0$. According to this dimensionless number, the output pressure P_c in the air bearing is solely influenced by the input pressure P. The pressure drops due to the diameters; mass density of the fluid and flow that are known to have an impact on the output pressure are not grasped by this initial computation. The computation is valid dimensionally but in practice some physical phenomena that nevertheless really impact the output pressure P_c are not integrated in the dimensionless number.

If the proposed heuristic is applied, another clustering emerges in Table 7. This leads to the following clustering minimizing the number of 0 in matrix A.

Table 7. Clustering matrix following the heuristic principle

Π_{P_C}		Influenced variables [B]	Influencing variables [A]		
		P_C	$P.d$	$f_o.h$	ρ
Base dimensions	L	-1	0	4	-3
	T	-2	-2	-1	0
	M	1	1	0	1

After applying the Cramer method the coefficient of the equation are computed and it leads to the following dimensionless number.

$$\Pi_{P_C} = P_C \cdot P^{-2} \cdot d^{-2} \cdot h^2 \cdot f_o^{\,2} \cdot \rho^1 \tag{4}$$

In this dimensionless number, all the variables are actively participating to the explanation of the phenomenon. It is also possible to see that the contribution to P_c is proportional to the value of the exponent, according to the rearranged equation below. P and d are participating positively to P_c when f_o and ρ are acting negatively. f_o as a bigger impact than ρ.

$$P_C = \Pi_{P_C} \cdot P^2 \cdot d^2 \cdot h^{-2} \cdot f_o^{\,-2} \cdot \rho^{-1} \tag{5}$$

The exponents give a direct evaluation of the contributions of individual variables to the target variable P_c. The exponent does not take into account the order of magnitude of the different variables of the equation.

Nevertheless the exponent consideration can be used further for qualitative considerations later. The present article is not taking benefit of this observation.

Another element that can be detected using this dimensional homogeneity approach is the evaluation of the completeness of a set of variables. For example, the variables influencing F_c in Fig. 7 are considered without taking into account the mass density of the fluid ρ. The Table 8 is directly resulting from Fig. 7 and is from Table 1 and 2.

The set of influencing variables is clearly inappropriate according the Cramer's rule. Indeed, D_I and D_E are generating two similar columns in A and consequently a null determinant. If those variables are combined, the matrix A becomes a 2x3 matrix. This implies that another variable should be added to the initial set of influencing variables from Fig. 7. This variable should contain base dimensions different from 0 for T (Time) or M (Mass). Several potential variables from our initial set of variables can influence Fc directly. The most probable variable is the fluid mass density ρ. This is resulting to Table 9 in which the proposed heuristic has been considered.

Table 8. Initial matrix for $\Pi_{F_C} = F_C \cdot D_E^{a4} \cdot D_I^{b4} \cdot P_C^{c4}$

Π_{F_C}		Influenced variables [B]	Influencing variables [A]		
		F_C	D_I	D_E	P_C
Base dimensions	L	1	1	1	-1
	T	-2	0	0	-2
	M	1	0	0	1

Table 9. Expended initial set of influencing variables by adjunction of ρ

Π_{F_C}		Influenced variables [B]	Influencing variables [A]		
		F_C	D_I, P_C	D_E	ρ
Base dimensions	L	1	0	1	-3
	T	-2	-2	0	0
	M	1	1	0	1

The computation using the Cramer's method is providing the following coefficients.

$$\Pi_{F_C} = F_C \cdot D_E^{-1} \cdot D_I^{-1} \cdot P_C^{-1} \cdot \rho^0 \tag{6}$$

The mass density ρ has a 0 coefficient. All the other valid combinations used for the clustering are providing the same results. This tend to prove that even if the addition of a new variable is necessary for applying the Cramer's rule, the added variable is not playing a role in the physical phenomena. This has been verified by checking that all the other combinations provide the same results.

For the two other dimensionless combinations presented in Table 2, Π_K and Π_{fo}, the same heuristic has been applied in order to minimize the number of 0 in matrix A. It seems that this principle is not sufficient; indeed different results can be found for Π_K and Π_{fo}. Some of these results will generate dimensionless groups where several parameters have a zero coefficient. The authors propose to add to the two heuristic rules a third rule in order to select the most appropriate result for the dimensionless groups when several potential results are available:

(3). The selected dimensionless groups should be chosen so that the number of exponents equal to 0 is minimized.

In the case of the air bearing, the rule seems to match well with the proposals made by the experts group. The two remaining computed dimensionless groups computed according to this heuristic are the following: $\Pi_K = K \cdot D_E^{-1} \cdot D_I^{-1} \cdot P_C^{-1} \cdot \rho^0$ and $\Pi_{f_o} = f_o \cdot d^{-1} \cdot P_{adm}^{-1} \cdot P_C^{-1} \cdot h^{-1} \cdot V_C^{-1}$.

6. Mathematic Approach to Propagate the Objectives

Mathematic tools have been developed by Bashkar and Nigam (Bashkar & Nigam, 1990) in order to analyse the interactions between variables forming a dimensionless product. The development of dimensionless groups in the previous section is used in this section to develop a propagation mechanism. The goal is to propagate the objectives set on the performance variables into the directed graphs generated in the previous stages. A specific dimensionless group can be expressed in the following manner according to Equation 7:

$$y_i = \Pi_k . x_j^{-\alpha_{ij}} . x_l^{-\alpha_{il}} . x_m^{-\alpha_{mi}} \tag{7}$$

This equation can be written:

$$\frac{y_i}{x_j} = \Pi_k \frac{x_j^{-\alpha_{ij}}}{x_j} . \frac{x_l^{-\alpha_{il}} . x_m^{-\alpha_{mi}}}{x_j} \tag{8}$$

The derivative of this dimensionless group has the form:

$$\frac{\partial y_i}{\partial x_j} = -\Pi_k \alpha_{ij} \frac{x_j^{-\alpha_{ij}}}{x_j} . \frac{x_l^{-\alpha_{il}} . x_m^{-\alpha_{mi}}}{x_j} \tag{9}$$

Consequently the derivative takes the general form:

$$\frac{\partial y_i}{\partial x_j} = -\alpha_{ij} \frac{y_i}{x_j} \tag{10}$$

Knowing the sign of the exponents, α_{ij}, the sign of the intra dimensionless group derivative can be determined by using the Equation 9. This information is precious to propagate backward the objectives set to the objective variables (i.e. the red variables) in the graph below.

Using the principles described above and by applying them to the dimensionless numbers defined in the previous section, it is possible to define the signs of the derivatives linking the different variables of the air bearing model presented above. For example, the objective to maximize F_c is propagated backward considering the dimensionless groups $\Pi_{F_C} = F_C \cdot D_E^{-1} \cdot D_I^{-1} \cdot P_C^{-1}$.

Using Equation 10, the following derivatives can be defined in equation 11, 12, and 13.

$$\frac{\partial F_C}{\partial D_E} = +1 \frac{F_C}{D_E} \tag{11}$$

$$\frac{\partial F_C}{\partial D_I} = +1 \frac{F_C}{D_I} \tag{12}$$

$$\frac{\partial F_C}{\partial P_C} = +1 \frac{F_C}{P_C} \tag{13}$$

The interpretation of the derivatives is the following; if we want to maximize F_c, there is also needs to maximize D_E, D_I and P_C.

Using the same principle, a conflict can be detected on *Pc*, due to the fact that the objective are simultaneously to minimize *fo*, the air leakage, to maximize *K* the air bearing stiffness and to maximize *Fc*, the loading capacity of the bearing. Starting from those 3 objectives and using the propagation mechanism

described above using Equation 7, it is resulting in a contradictory objective on *Pc* that should be minimized to limit the leakages *fo*, and that should be maximized to maximize the stiffness *K* and the load capacity *Fc*.

The same principle is applied on all the other 5 dimensionless groups computed in the previous section. The Fig. 10 has been derived from this calculation. The propagation method has been applied in this example to the design variables in green and blue but not for the non-controlled variables in black.

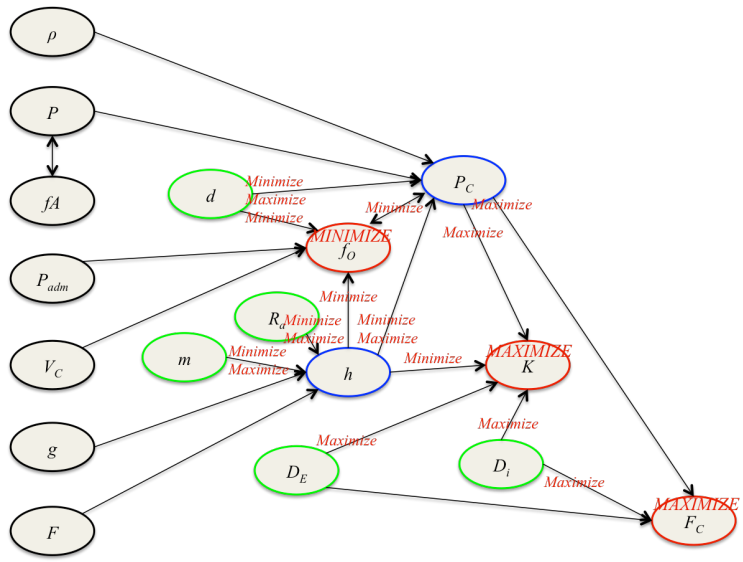

Fig. 10. Graph of the air bearing interactions with objectives on performance variables and propagation backward in the oriented graph.

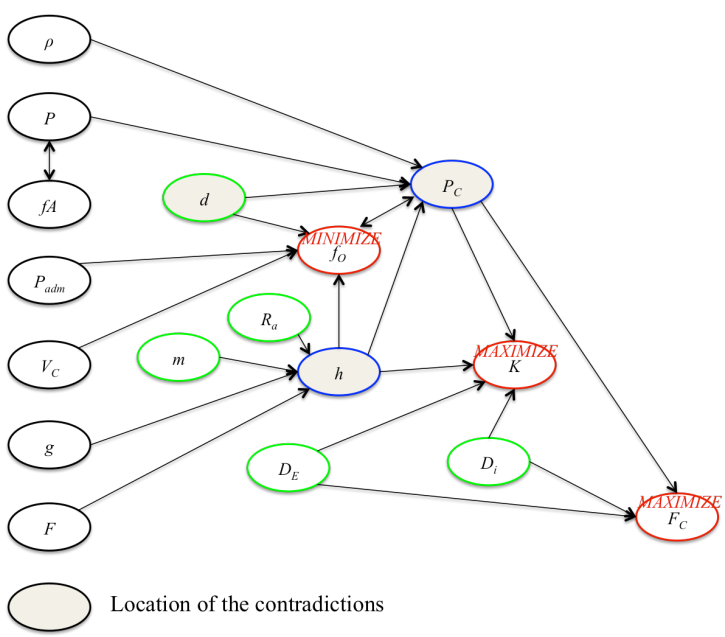

Fig. 11. Visualization of the major contradictions in the air bearing design.

In Fig. 11, the propagation backward from the objectives set to the objective variables (i.e. red variables) are also generating objectives on the other variables such as the design variables (i.e. blue and green

variables). If contradictory objectives are resulting from these propagations, it is resulting in a physical contradiction. The Fig. 10 can be simplified to show more explicitly the main contradictions (see Fig. 11).

The next step of the analysis consists of listing and selecting between the different design strategies that can be used to overcome those three major contradictions in the design of air bearings. This work has already been done inside our research group. It is not presented in this paper but is the topic of publications under preparation at the moment.

7. Results

This section presents the prototype software tool developed for applying the method presented in the above sections. The causal ordering graph of the air bearing system was obtained by a group work composed of experts. The experts selected an initial set of 17 variables and 23 cause-effect relations between them using the approach presented in sections 3.2 and 3.3. This graph has been modelled using a parametric diagram from the SysML language modelled using the Topcase software as shown in Fig. 12. Each design variable was represented in a block containing its dimensional representation in form of a composition of mass (*M*), length (*L*), and time (*T*). Each cause-effect relation is represented by an arrow *<<dependency>>* that indicates a source influenced by a client.

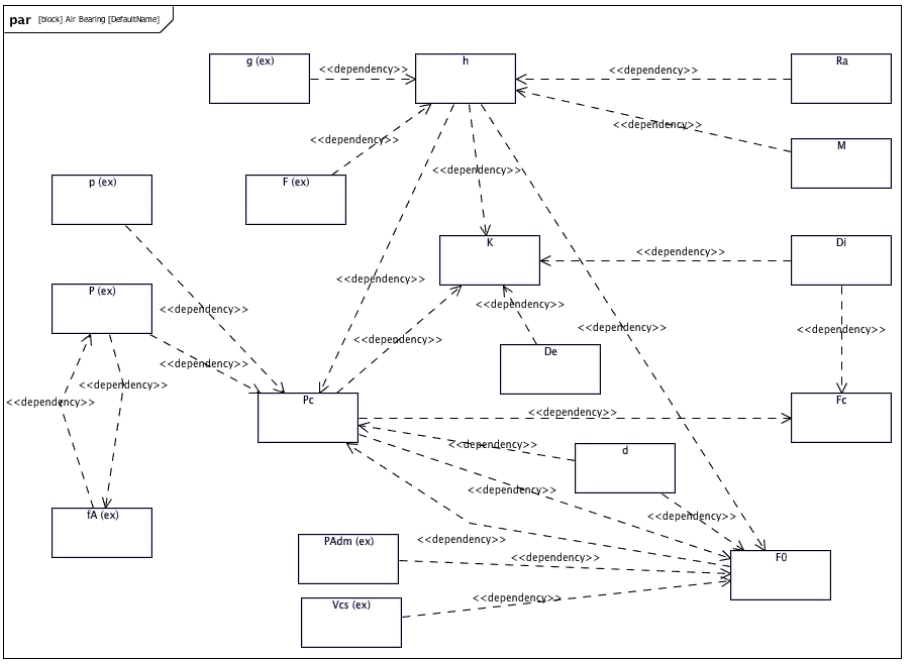

Fig. 12. Parametric diagram in SysML.

This SysML model was uploaded into the specific software tool developed during this research in form of a XMI file. The Fig. 13 shows the translation of the Fig. 12 into a more traditional causal graph between the system variables.

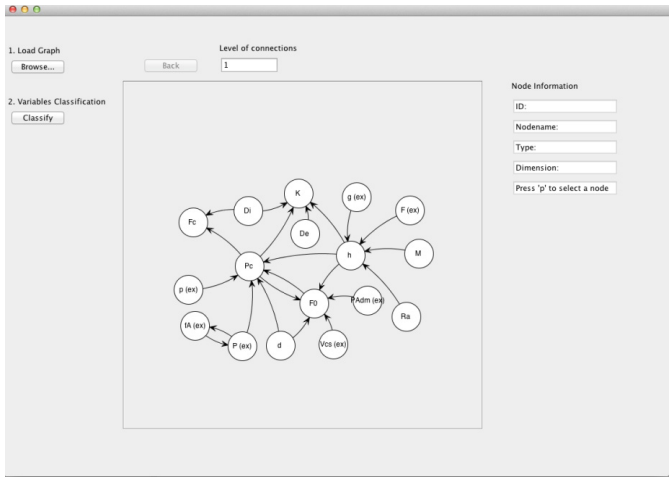

Fig. 13. Variables and their relationships represented in a directed acyclic graph (DAG).

The Direct Acyclic Graph of Fig. 13 is clustered using the colouring approach described in section 4. This is leading to the Fig. 14 where the performance variables are presented in red. The design variables are presented in green for the variables easier to control and in blue for the variables harder to control. The black variables are representing the exogenous variables (i.e. variables not included in the system boundaries).

Four variables, the, air bearing stiffness (K), the lifting force (F_c), the output airflow (f_o) and the output pressure (P_c) have been classified by the algorithm in the performance category.

The following step consists to define qualitative objectives for those four performance variables and then to propagate the objectives in the network. The propagation algorithm is not described in this article.

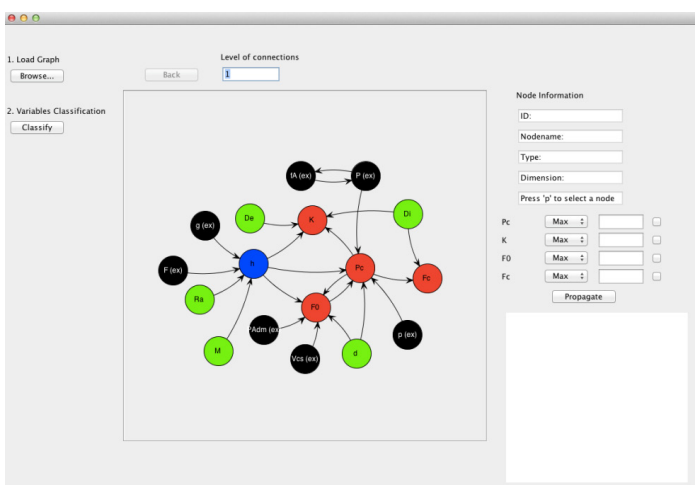

Fig. 14. Colouring variable nodes based on the variable types.

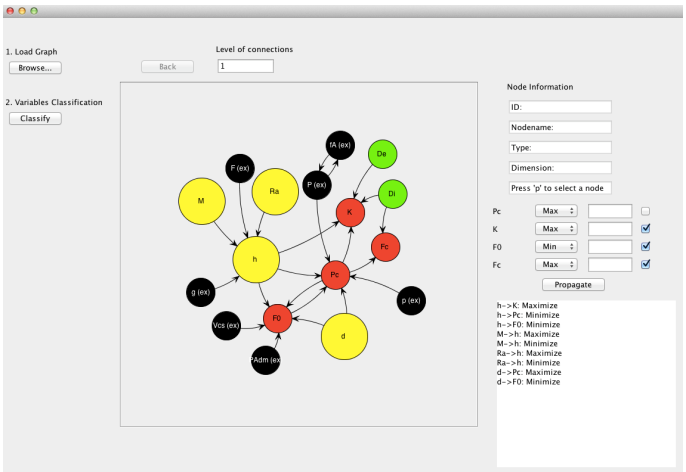

Fig. 15. Contradiction graph.

The conflicting nodes resulting from the propagation mechanism are represented in yellow in Fig. 15.

A slight difference exist between Figure 11 and Figure 15. This is due both to the representation of more layers of contradictions in Figure 15 and also to the choice of the user to integrate Pc in the set of performance variables. In Figure 15, the conflicting nodes are also including the second layer of conflicts with *m* and *Ra*. In Figure 11, this second layer of conflicts have not been taken into account but those contradictions are also existing in Figure 10. In the Figures 14 and 15, it has been decided by the user of the software tool to integrate *Pc* in the set of the performance variables of the problem. This is not the case in Figures 10 and 11.

d injection nozzle diameter d should be simultaneously as small as possible and also as big as possible. This is clearly a conflicting requirement on the variable.

8. Discussion

The approach developed in this article is offering the first stages of a method supported by a computer analysis tool for systematically highlighting physical contradictions. The authors claim that the future possibilities embedded in the present research in terms of systematic mapping of design strategies are important. For example initial analyses made by the research team tend to show that radical improvements for mature products or components such as the air bearing used in this article can only be obtained not by tacking directly the specific contradictions highlighted by the computer tool but instead by modifying the borders of the system. This can be done by finding ways to control variables that are hard or seems impossible to control such as the exogenous variables. For example in the case of the air bearing it might be extremely fruitful if a variable like the atmospheric pressure (P_{adm}) can become controllable.

For New Product Development and not very mature products and services, a great field of improvement can come from solving directly contradictions discovered with this tool. Another research exploration can consist of listing all the potential design strategies that can be employed and most importantly to evaluate the potential impact associated with the usage of a certain design strategy.

In the present article the causal ordering has been obtained by the contribution of a group of experts applying manually the causal ordering methods described in the section 3 of this article. An automatic causal ordering algorithm has also been developed and is currently tested. This automatic causal ordering represents a significant improvement and will be presented in a future publication.

The types of contradictions addressed directly in the case study of the article are the physical contradictions which are the ones visible at the most detailed level of representation of system architecture. Nevertheless different levels of granularity in the systems representation can be presented and the future

developments will also develop an approach to compose the elementary contradictions to highlight the higher level contradictions and weaknesses at system level.

Another line of research will be potentially very valuable. The causal graphs can be used for modularizing the modelling and simulation process and for quality checking of the models will be to form a repository of elementary components and sub-systems. The components and sub-systems will be represented in form of causal graphs including automatic checking of the dimensional validity and of the elementary behaviours.

The similarity principle included in the dimensional analysis theory can provide ground for interchangeability analysis of components and subsystems but also for reusability of models parts.

The main interest of the present article is lying in the fact that this research work is trying to develop connections between different methods and approaches to form a coherent whole that can be supported by means of interactive computer tools. In this work, the authors have tried to demonstrate that TRIZ, graph theory and dimensional analysis can form parts of a coherent holistic approach supporting the design process.

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References

Altshuller, G. (1984). *Creativity as an exact science.* Gordon & Breach, Luxembourg.

Barenblatt, G. I. (1979). *Similarity, Self-similarity and Intermediate Asymptotics*. Consultant Bureau, Plenum, New York.

Basseches, M. (1980). Dialectical schemata: A framework for the empirical study of the development of dialectical thinking. *Human Development, 23*, 400-421.

Basseches, M. (2005). The Development of Dialectical Thinking as an Approach to Integration. *Integral Review, 1,* 47-63.

Bhashkar, R., & Nigam, A. (1990). Qualitative physics using dimensional analysis. *Artificial Intelligence, 45*, 73-111.

Coatanéa, E. (2005). Conceptual Modelling of Life Cycle Design: A Modelling and Evaluation Method Based on Analogies and Dimensionless Numbers, PhD dissertation, ISBN 951-22-7853-7, ISBN 951-22-7852-9.

Cromer, A. (1993). Uncommon sense: The heretical nature of science. *New York: Oxford University Press*.

Godet, M., Durance, P., & Gerber, A. (2006). Strategic Foresight: Use and Misuse of Scenario Building, LIPSOR Working Paper, (en.laprospective.fr/dyn/anglais/ouvrages/sr10veng.pdf).

Goldratt, E. M. (1998). Late Night Discussions on the Theory of Constraints. *North River Press*.

Hirtz, J. Stone R. B., McAdams, D. A., Szykman, S. & Wood, K. L. (2002). A functional basis for engineering design: Reconciling and evolving previous efforts. *Research in Engineering Design, 13*, 65–82.

INCOSE (2010). Systems Engineering Handbook V3.2, INCOSE Editor.

Kahneman, D. (2011). Thinking fast and flow. *Penguin books*.

Matz, W. (1959). Le principe de similitude en Génie Chimique. *Dunod, Paris.*

Medyna, G., Nonsiri, S., Coatanea, E., & Bernard, A. (2012). Modelling, Evaluation and Simulation during the Early Design Stages: Toward the Development of an Approach Limiting the Need for Specific Knowledge. *Transaction of SDPS: Journal of Integrated Design and Process Science, 16*(3), 83-103.

Nakamura, H. (1964/1985). Ways of thinking of Eastern peoples: India, China, Tibet, Japan. *Honolulu: East-West Center Press.*

Newman, M. E. J. (2010). Networks: An Introduction. *Oxford: Oxford University Press*, ISBN 0-19-920665-1.

Peng, K., & Nisbett, R. E. (1999). Culture, dialectics, and reasoning about contradiction. *American Psychologist*, *54*(9), 741-754.

Shen, Q., Peng, T. (2006). Combining Dimensional Analysis and Heuristics for Causal Ordering. In A. Bundy and S. Wilson (Eds), *Memory of Dr RobMilne – Rob Milne: A Tribute to a Pioneering AI Scientist, Entrepreneur and Mountaineer* (pp 39-53). IOS Press.

Sonin A.A. (2001). The physical basis of dimensional analysis, 2nd edition. *Department of Mechanical Engineering MIT Cambridge, MA 02139.*

Savransky, S. D. (2001). Engineering of creativity - Introduction to TRIZ methodology to inventive problem solving. *CRC Press, New York*, ISBN 0-8493-2255-3.

Shim, T. (2002). Introduction to physical system modelling using bond graphs. *University of Michigan-Dearborn.*

Wilson, P. F., Dell, L. D., and Anderson, G. F. (1993). Root cause analysis: a tool for total quality management. *ASQC Quality Press, Milwaukee*.

Yan, B., Zeng, Y. (2011). Design Conflict: Conceptual Structure and Mathematical Representation. *Transaction of SDPS: Journal of Integrated Design and Process Science*, *15*(1), 75-89.

Author Biographies

Eric Coatanéa has received is double doctoral degree in Engineering design in October 2005 from Helsinki University of Technology in Finland (nowadays Aalto University) and from University of West Brittany (France). Before embarking in doctoral studies, Eric Coatanéa has worked during 11 years has a manufacturing engineering teacher in University of West Brittany. He studied in University of West Brittany, INSA Toulouse and in Ecole Normale Supérieure Cachan. From 2005 to 2007, he has been a Marie Curie fellow. From 2008 to 2013, he has been fixed term professor of product development in Aalto University where he has established a new research group with a focus on modelling, simulation and decision making at early development stages with a system perspective.

Sarayut Nonsiri is member of Dynavio and a doctoral student at Aalto University School of Engineering, Department of Engineering Design and Production. His research work focuses on investigating in both theory and application for modelling and simulation during the early stages of the design process, model-based systems engineering, computation algorithm, and artificial intelligence areas.

Ricardo Roca was the Deputy Director for Joint Assessment and Enabling Capability (JAEC), Modelling & Simulation Branch Training, Readiness and Strategy Directorate Personnel and Readiness at the Office of the Secretary of Defence, U.S. Department of Defence. He is currently researcher at The Johns Hopkins University Applied Physics Laboratory.

Faisal Mokammel is member of Dynavio and a doctoral student at Aalto University School of Engineering, Department of Engineering Design and Production. He received M.Sc. degree in electrical engineering from Dalarna University, Sweden. Since 2011, he is member of product development research group, led by Dr. Eric Coatanéa. Mokammel is working on early stages of the design process mainly requirement engineering using natural language processing, graph theory and computational algorithm.

Juliane Kruck is a Master student in Karlsruhe University. Juliane has been involved with this research work during her internship at Finland.

François Christophe is a post-doctoral researcher at Tampere University of Technology. His former research was focused on Knowledge Representation and semi-formal modelling.