Conceptual analysis of complex system simulation data for decision support: Application to aircraft cabin design

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Abstract. This paper presents a conceptual approach for decision support applied in a collaborative complex system design project. The approach takes advantage of the use of Similarity-based Formal Concept Analysis (SFCA) to classify, visualize, and explore simulation data in order to help system designers to identify relevant design choices. The approach is illustrated on an aircraft cabin design case study which concerns the simulation of different configurations of the ventilation system to study the passengers comfort in the cabin. The classification of simulation data with their corresponding comfort scores using SFCA allows to derive for each simulated input parameter the maximal interval of values which guarantee an acceptable comfort level. To evaluate the obtained results, the extracted intervals are then used as ranges of the input parameters for new simulations which confirmed the already obtained comfort levels and showed the convergence of the results.

1 Introduction

The design phase is one of the biggest challenges industrial companies are often facing in complex system production process. During the design process, several aspects must be studied to ensure the system performances as well as its compliance with the end-user requirements. These aspects are reflected by a set of design parameters that must be taken into account early from the design phase. Several simulations of design parameters are then performed before validating the design choices. In the case of complex systems, simulations produce large datasets to be carefully studied and analysed in order to identify optimal configurations. The analysis process simultaneously implies several criteria and is usually defined as multiple criteria decision analysis (MCDA) task which involves the comparison and ranking of a number of alternatives with respect to multiple, potentially conflicting, criteria, with the ultimate objective of identifying the best option from the available choices [1]. In this context, decision support tools are used to aid decision-makers to make rational choices. The range of decision support methods is very large and covers several application domains such as economy, industry, etc. [2, 3]. The choice of one method instead of another depends on several constraints related to data characteristics (data format, data size, etc.) or to the method it-self as generated result characteristics (visualization, analytics, etc.). In [1], a brief survey of

the main decision support approaches in industrial contexts is given before introducing an approach based on rough sets for environmental decision support in industry. In the current work we are particularly interested in decision support approaches based on conceptual structures such as concept lattices derived based on Formal Concept Analysis (FCA) formalism [4]. These approaches are motivated by the richness of lattice structures as well as by their well-established formal properties. Indeed, a concept lattice is a conceptual representation of data that highlights its underlying structure and implicit relationships. Its usefulness for data analysis purposes is proved by the large number of derived approaches which used lattice structures as navigation support for information retrieval, as condensed representation of itemsets, implications and association rules for data mining, as a set of embedded decision trees for machine learning, prediction and decision support, etc. [5]. However, FCA method is usually limited by the rigidity of its input format (binary data). Some works have proposed to extend it to complex data [6–8], among them Similarity-based Formal Concept Analysis (SFCA) method which considers similarity to directly classify non-binary data into lattice structures called Many-Valued Concept Lattices (MV lattices) [8]. Besides extending FCA to complex data and avoiding loose of information in transformation phases, SFCA classification process produces MV lattices with different granularity levels which allows progressive data exploration [9].

In this paper we study the usefulness of MV lattices to provide a support for combining numerical values (quantitative) analysis together with qualitative analysis to aid decision makers in the process of complex system Design. More precisely we show how MV lattices can be used to highlight crucial information a designer may need to validate design choices. The proposed approach is applied to an industrial case study: the design of the ventilation system of an aircraft cabin. Simulation data for this case study are classified and analysed using MV lattices to identify relevant design configurations regarding the obtained passengers comfort in the cabin. The analysis is facilitated by two visualization techniques proposed in this work: score-based and interval-based visualization. The rest of the paper is organized as follows: Section 2 presents the context of the study and the aircraft cabin design test case. Section 3 recalls basic definitions of SFCA. Section 4 briefly describes the two visualization techniques to aid decision making in MV lattices. Section 5 details the application of SFCA to the aircraft cabin case, the obtained results and an evaluation of these results followed by the conclusion in Section 6.

2   Context of the Study: Collaborative Complex System Design

The present research work is part of the Complex System Design Lab (CSDL)[3] project which involves 27 industrial and academic partners and aims at providing a collaborative environment for complex system design. Since the simulation of design choices, which is one of the more strategic steps of complex system design, usually outputs large and high dimensional datasets, the CSDL platform should allow efficient analysis of such datasets to identify the right conception choices. In this project, simulations are

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[3] http://www.systematic-paris-region.org/fr/projets/csdl

performed following a Design of Experiment procedure which consists in computing the systems outputs for a set of chosen design points of parameter space. Moreover, additional data dealing with the systems performances such as performance criteria, cost functions and constraints are computed. Then the objective of the analysis step is to identify interesting regions of the parameters space which correspond to the appropriate design configuration.
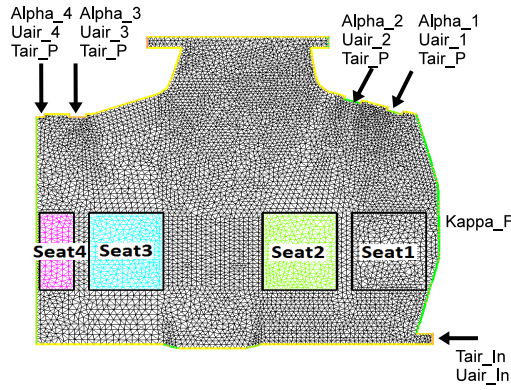

Fig. 1: Aircraft cabin schema and the main simulated input parameters

Parameter	Range
Alpha_1 (°)	[-90, -80]
Alpha_2 (°)	[-100, -45]
Alpha_3 (°)	[-135, -90]
Alpha_4 (°)	[-120, -80]
Uair_1 (m/s)	[0.2, 0.7]
Uair_2 (m/s)	[0.2, 0.7]
Uair_3 (m/s)	[0.2, 0.7]
Uair_4 (m/s)	[0.2, 0.7]
Uair_In (m/s)	[0.6, 3]
Tair_In ($°C$)	[22, 25]
Tair_P ($°C$)	[22, 25]
T_ext ($°C$)	[-65, -50]
Kappa_F (W/K)	[1 e^{-4}, 4 e^{-4}]

Table 1: Ranges of the simulated parameters

CSDL industrial partners have provided a use case which corresponds to a commercial aircraft cabin air control system. In this use case the goal is to identify relevant design configurations which ensure comfort conditions in terms of air temperature and velocity inside the cabin. Typical fields of temperature and velocity are obtained using the same fluid model as in [10] and the comfort design problem is parametrized by 13 continuous parameters each evolving in a range interval of possible values (see Table 1). These design parameters are: angles of air injection at 4 passengers' personal fan (Alpha_1..4), blown air speed at 4 passengers' personal fan (Uair_1..4), temperature of blown air at main inlet (Tair_In), temperature of blown air at 4 passengers' personal fan (Tair_P), blown air speed at main inlet (Uair_In), external temperature (T_ext), and fuselage thermal conductivity (Kappa_F). The mean values of temperature and velocity for each of the four passengers' seats (see Figure 1) have been computed to assess the passengers' comfort, which resulted in eight output criteria (two per passenger) related to the comfort. Moreover, a measure of the energy consumed by the air-conditioning system is also considered to estimate the price at which this comfort comes.

In the reminder of this paper we propose an approach based on SFCA for data analysis and decision support in industrial contexts through the classification and visualization of simulation datasets. The approach is illustrated on the previously introduced CSDL use case.

3   Similarity-Based Formal Concept Analysis Basic Notions

SFCA [8, 9] is a classification and data analysis method which extends FCA definitions and results to complex data represented by *many-valued contexts* [4]. Formally, an MV context is denoted by (G, M, W, I) where G is a set of objects, M is a set of attributes, W is a set of attribute values, and I is a ternary relation between G, M and W (i.e., $I \subseteq G \times M \times W$). $(g, m, w) \in I$ denotes the fact that "*the MV attribute m takes the value w for the object g*". This fact is also denoted by $m(g) = w$. Table 2 gives an example of MV context corresponding to a part of simulation results for the aircraft cabin test case (Figure 1). In this example, objects correspond to the first 5 simulations and the attributes correspond to a part of simulated input parameters, namely T_Ext, Tair_In, Tair_P, and Uair_In, and two output parameters T1 and V1 respectively corresponding to the air temperature and velocity in seat1.

Table 2: An example of Many-valued Context corresponding to a part of simulation results for seat1 in the aircraft cabin test case.

	T_Ext ($°C$)	Tair_In ($°C$)	Tair_P ($°C$)	Uair_In (m/s)	T1 ($°C$)	V1 ($10^{-2}m/s$)
1	-57.41	23.89	23.31	2.56	23.86	1.31
2	-56.68	22.71	23.11	1.95	22.34	3.47
3	-59.38	24.27	23.39	2.72	24.01	6.68
4	-51.11	22.06	23.95	1.78	21.42	2.38
5	-55.93	24.28	23.70	2.25	23.91	3.43

The basic intuition of SFCA is to group together objects which are sufficiently similar (i.e. have similar attribute values). Therefore, a set of objects A shares an attribute m when all values of m for the objects in A are similar. The similarity is defined in the common intuitive way: two values are similar when their difference is not significant. In the case of numerical data, computing similarity is straightforwardly given by a comparaison of the numerical values. Two values are said to be similar if their difference is less than a given similarity threshold θ which expresses the maximal variation allowed between two similar values. Formally, given a numerical MV context (G, M, I, W) and $w_i, w_j \in W$, $w_i \simeq w_j$ iff $|w_i - w_j| \leq \theta$. More generally, two intervals $[\alpha_1, \beta_1]$ and $[\alpha_2, \beta_2]$ are similar iff $max(\beta_1, \beta_2) - min(\alpha_1, \alpha_2) \leq \theta$. Given a similarity threshold θ, the set of all possible possible intervals of similar values that can be defined on W, denoted by $\mathfrak{I}_\theta$, is the set of intervals of the form $[w_i, w_j]$ such that $w_i, w_j \in W$ and $w_j - w_i \leq \theta$.

The choice of θ reflects the precision requirements to be considered during the data analysis process. Lower values of θ mean that only the closest values will be considered as similar whereas higher values of θ mean that more distant values can be considered as similar. Depending on considered datasets and on the analysis processes, it is possible to choose either the same similarity thresholds for all the context attributes or a separate

threshold for each attribute. In the later case, θ denotes a vector $(\theta_i)_{0 \leq i < |M|}$ of $|M|$ elementary thresholds respectively corresponding to the context attributes.

Based on the similarity of attribute values, SFCA extends the definition of attribute sharing between objects as follows. Given two objects $g_i, g_j \in G$ and an attribute $m \in M$ such that $m(g_i) = w_i$ and $m(g_j) = w_j$, g_i and g_j share m whenever $w_i \simeq w_j$. The interval of values $[min(w_i, w_j), max(w_i, w_j)]$ is called *similarity interval* of attribute m for objects g_i and g_j. Then g_i and g_j are said to share m w.r.t to $[min(w_i, w_j), max(w_i, w_j)]$ written as $(m, [min(w_i, w_j), max(w_i, w_j)])$. More generally, a set of objects A shares $(m, [\alpha, \beta])$ where $\alpha = min_{g \in A}(m(g))$ and $\beta = max_{g \in A}(m(g))$ whenever $\forall g_i, g_j \in A$, $m(g_i) \simeq m(g_j)$. In this case, A is said to be *valid* w.r.t. m and $[\alpha, \beta]$ is the similarity interval of m for A. In the same way, A shares a set of attributes B whenever A shares all attributes in B. In the MV context given in Table 2 objects 1 and 3 share attribute T1 for a similarity threshold $\theta_4 = 1$. However these two objects do not share attribute V1 for $\theta_5 = 1$.

A *many-valued concept* is defined as (i) maximal sets of objects having in common (ii) maximal sets of attributes with intervals of similar values. These sets are formally defined as follows.

(i) *Maximal valid sets of objects*: Given an attribute m and a set of objects A valid w.r.t. m. SFCA defines the set of reachable objects from A w.r.t. m as :

$$\mathfrak{R}(A, m) = \{g_i \in G \mid m(g_i) \simeq m(g), \ \forall g \in A\}$$

$\mathfrak{R}(A, m)$ is the maximal set containing all objects similar to those in A w.r.t. m. This set may not be valid w.r.t. m because of the non transitivity of "$\simeq$". The maximal valid set of objects containing A is the subset of $\mathfrak{R}(A, m)$ obtained by removing from $\mathfrak{R}(A, m)$ all pairs of objects which do not share m. Formally this set is defined as follows:

$$\mathfrak{R}_v(A, m) = \mathfrak{R}(A, m) \setminus \{g_i, g_j \in \mathfrak{R}(A, m) \mid m(g_i) \not\simeq m(g_j)\}$$

More generally, the maximal valid set containing A with respect to $B \subseteq M$ is:

$$\mathfrak{R}_v(A, B) = \bigcap_{m \in B} \mathfrak{R}_v(A, m)$$

(ii) *Maximal intervals of similar attribute values*: When $A \subseteq G$ shares an attribute $m \in M$, the largest interval of similar values of m for A is the interval of similar values of m for the objects in $\mathfrak{R}_v(A, m)$ obtained as follows:

$$\gamma(A, m) = [min_{g \in \mathfrak{R}_v(A,m)}(m(g)), max_{g \in \mathfrak{R}_v(A,m)}(m(g))]$$

Then A is said to share $(m, \gamma(A, m))$. For example, for $\theta_0 = 1$, the set of objects $\{1,3,5\}$ shares $(T1, [23.86, 24.01])$.

Based on these maximal sets, SFCA defines the following derivation operators for $A \subseteq G$ and $B \subseteq M \times \mathfrak{I}_\theta$:

$$A^\uparrow = \{(m, \gamma(A, m)) \in M \times \mathfrak{I}_\theta \mid \gamma(A, m) \neq \emptyset\}$$

$$B^\downarrow = \mathfrak{R}_v(\{g \in G \mid \forall (m, [\alpha, \beta]) \in B, \ m(g) \simeq [\alpha, \beta]\}, B)$$

$A^\uparrow$ is the maximal set of MV attributes shared by all objects in A and $B^\downarrow$ is the maximal set of objects sharing all MV attributes in B. It has been shown in [8, 9] that $\uparrow$ and $\downarrow$ form a Galois connection between $(G, \subseteq)$ and $(M \times \mathfrak{I}_\theta, \subseteq_\theta)$.

In the example of MV context in Table 2, and for $\theta = (10, 10, 10, 10, 1, 1)$, we have:
$\{1, 3, 5\}^\uparrow = \{(T1, [23.86, 24.01]), (T\_Ext, [-59.38, -55.93]), (Tair\_In, [23.89, 24.28]),$
$(Tair\_P, [23.31, 23.7]), (Uair\_In, [2.25, 2.72])\}$
and
$\{(T1, [23.86, 24.01]), (T\_Ext, [-59.38, -55.93]), (Tair\_In, [23.89, 24.28]), (Tair\_P,$
$[23.31, 23.7]), (Uair\_In, [2.25, 2.72])\}^\downarrow = \{1, 3, 5\}$.

MV concepts are then defined as pairs (A, B) where $A \subseteq G$ and $B \subseteq M \times \mathfrak{I}_\theta$ such that $A^\uparrow = B$ and $B^\downarrow = A$. A and B are respectively the extent and the intent of (A, B). For $\theta = (10, 10, 10, 10, 1, 1)$ in the MV context given in Table 2, $(\{1, 2, 3\}, \{(T1, [23.86, 24.01]),$ $(T\_Ext, [-59.38, -55.93]),$ $(Tair\_In, [23.89, 24.28]), (Tair\_P, [23.31, 23.7]),$ $(Uair\_In,$ $[2.25, 2.72])\})$ is an example of MV concept.

The MV concepts of an MV context can be partially ordered based on the inclusion of their extents (and, dually, intents) and form the hierarchy structure called *MV concept lattice* and denoted by $\underline{\mathfrak{B}}_\theta(G, M, W, I)$. The Hasse diagram of the MV concept lattice of the MV context given in Table 2 for $\theta = (10, 10, 10, 10, 1, 1)$ is shown in Figure 2. In this graphical representation, MV attributes in the form $(m, [\alpha, \beta])$ are written $m : [\alpha, \beta]$ for a better readability.
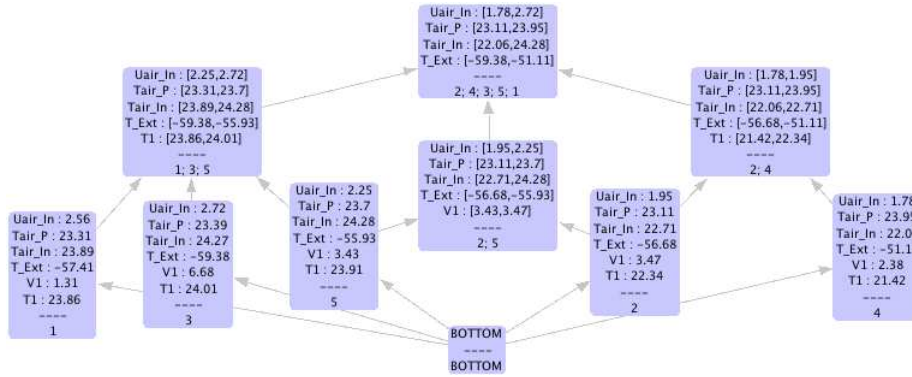

Fig. 2: The MV lattice $\underline{\mathfrak{B}}_\theta(G, M, W, I)$ corresponding to the MV context given in Table 2 for $\theta = (10, 10, 10, 10, 1, 1)$.

4   Visualization of MV Concepts

Finding patterns within MV concepts may be assisted with the use of visualization techniques. In this work we propose two techniques to assist the analyst in determining

the similarity threshold, filtering and selecting concepts of interest. The proposed techniques follow the so called "information-seeking mantra" - Overview first, zoom and filter, then details-on-demand [11].

First we propose a visualization technique that consists on the filtering and coloring of concepts based on user-defined scores. In Section 2, we show how certain intervals in the temperature and the air speed are used to determine comfort classes in the cabin according to international standards. A color gradient is assigned according to the "global score" of a concept (Figure 2). For instance, the score of "maximum comfort" is attributed when the scores of velocity and and temperature are equal to 2 and the color. This simplification is important because in Complex System Design the number of parameters are usually overwhelming to the analyst to overview and compare. Alternatively, user can filter concepts that are below a score threshold. This is particularly important during the extraction of comfort classes as explained in Section 2.

When the relevant concepts are identified, i.e. the comfort classes in our case, the analyst will take decisions based on concepts that fit best to his or her goals. To help the analyst to quick identify intervals in the concepts and compare with other concepts in the lattice, we created a new visualisation based on a "conceptual heat map" where each concept is depicted as an array of rectangles (Figure 3). Each rectangle represents an attribute, its color indicates the interval of the attribute value in a continuous color scale from blue to red. Its width is proportional to the size of the range. If an attribute is not present in the concept the corresponding rectangle is empty in order to keep the order of attributes consistent.

5   Applying SFCA to Aircraft Cabin Test Case

5.1   Using Similarity Threshold to Express Constraints to Guide Data Exploration Process

In the previous section, SFCA formalisation is given from a numerical data perspective. Such a formalisation can also be done on other data formats which makes SFCA approach generic and flexible. In this case, appropriate similarity measures need to be defined accordingly to handle complex data. Once similarity measures are defined, the application of SFCA follows the intuition of "grouping together similar data". As shown above, this operation also needs the definition of threshold which can be a subjective task strongly related to the data analysis process. The variation of similarity thresholds yields a variation in the obtained MV lattices in terms of number of MV concepts as well as in terms of concept granularity and it has been shown that both aspects are related [9].

In the current work, we are interested in identifying the input requirements which guarantee a convenient output situations based on a set of simulation data. This means that we first need to formulate "convenient" output situations in terms of constraints. Then, we use such constraints to guide the SFCA classification process in order to obtain the appropriate values of input parameters satisfying these constraints. In the previously shown example (Table 2 and Figure 2) the choice of the threshold $\theta = (10, 10, 10, 10, 1, 1)$ follows the idea of defining constraints on the output parameters $T1$
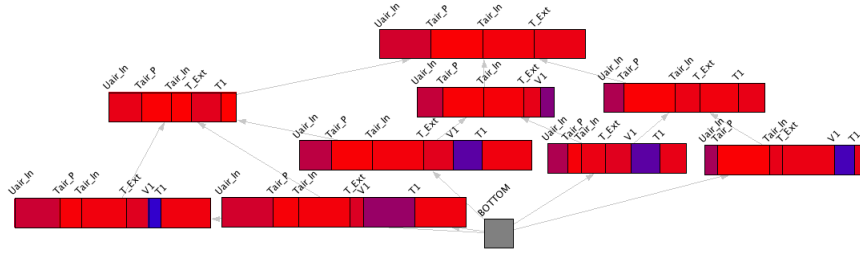
Fig. 3: The MV concept view for the lattice in Figure 2. Color indicates position in the range (from blue to red), width shows the length of the interval.

and $V1$ in order to extract the appropriate ranges of the input parameters T_Ext, $Tair\_In$, $Tair\_P$ and $Uair\_In$. Indeed, value of $\theta_i = 10$ defined as threshold for each input parameter exceeds the difference between the minimal and the maximal values of each of the four input parameters. Consequently, there is no effective constraint in grouping together these parameters while forming the MV concepts. However, the thresholds $\theta_i = 1$ for $T1$ and $V1$ mean that values of $T1$ (respectively $V1$) can be grouped together if and only if their difference is less than 1. This constraint is expressed to obtain a lattice formed by MV concepts where intervals of values of $T1$ and $V1$ are not larger than 1 and without any constraint on the other attributes. Having such a MV lattice one can directly read the maximal range of each input parameter which allows to obtain a temperature in given interval. For example, MV concept with extent $\{2,4\}$ in Figure 2 shows that values of $Uair\_In$, $Tair\_P$, $Tair\_In$ and T_ext respectively in intervals [1.78,1.95], [23.11,23.95], [22.6,22.71], and [-56.68,-51.11] ensure to obtain a value of T1 in [21.42,22.34]. Knowing intervals of temperature values corresponding to a comfort situation, it is then possible to deduce the required inputs to ensure such a comfort. Based on this idea we develop and apply a data analysis strategy to deal with the aircraft cabin design test case.

5.2   Simulation Dataset of the Aircraft Cabin Test Case

In the reminder of this paper we will consider the previously introduced aircraft design case study. The considered dataset corresponds to the simulation results of 100 randomly chosen configurations of design parameters (the 13 input parameters). 9 output criteria have been defined to assess the quality of each configuration in terms of passengers comfort and energy cost. The mean values of temperature and velocity of each of the four seats are computed which resulted in 8 criteria associated with the comfort of the passengers. The dissipated energy is computed based on the velocity as a measure of the loss of energy due to the fluid viscosity.

In order to quickly appreciate the comfort in each seat and hence simplify the dataset exploration and the experiments evaluation, comfort scores were computed for the values of the comfort output criteria (temperature and velocity). The scores are in a three points scale (0: uncomfortable, 1: acceptable, 2: comfortable) computed according to

ANSI/ASHRAE Standards [12] as follows:

$$\text{score(T)} = \begin{cases} 0 \text{ if } T < 21 \text{ or } T > 24 \\ 1 \text{ if } 21 \leq T < 22.5 \text{ or } 23.5 < T \leq 24 \\ 2 \text{ if } 22.5 \leq T \leq 23.5 \end{cases} \quad \text{score(V)} = \begin{cases} 0 \text{ if } V > 1 \\ 1 \text{ if } 0.2 < V \leq 1 \\ 2 \text{ if } V \leq 0.2 \end{cases}$$

These scores are then used instead of their corresponding values of temperature and velocity in the classification process by SFCA.

5.3 Extracting Comfort Classes and Their Corresponding Design Parameters' Ranges

Our objective is to determine the design parameters that are important to qualify the experiments such that all of the four passengers are satisfied. We make the assumption that the temperature is more important than the velocity to define the thermal comfort of the passengers. Therefore, we focus our analysis on the experiments that offer the maximum comfort for the passengers from the temperature point of view only: we keep only the experiments such that the score for the temperature is 2 and we called this subset S_{silver}. Then, following the previously detailed strategy for thresholds choice, we applied SFCA to build the corresponding MV lattice shown on Figure 4.
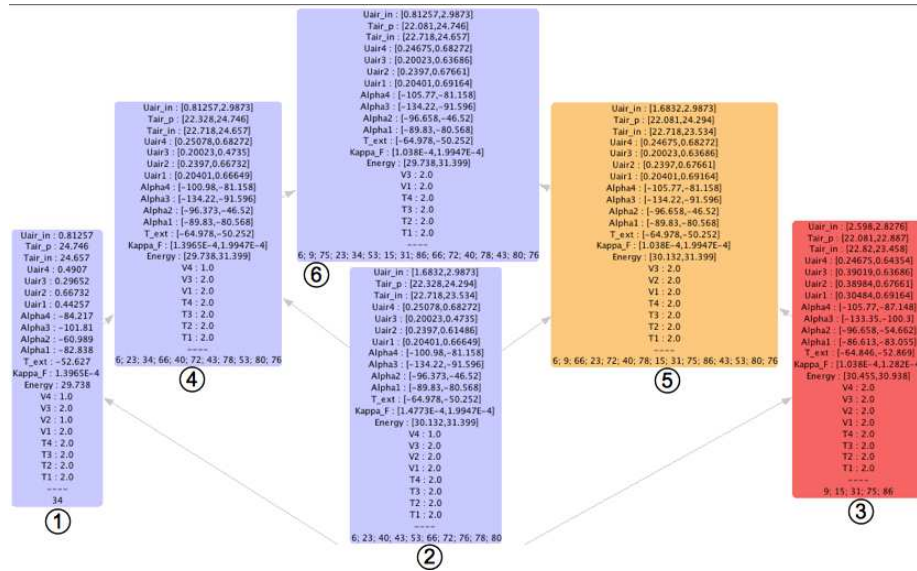

Fig. 4: MV lattice generated on S_{silver}

By analyzing this MV lattice, it turns out that S_{silver} can be described using three distinct main comfort classes: (i) "*Maximum comfort*" (concept $n°3$): maximum score

for both temperature and velocity for the 4 seats, (ii) "*Intermediate comfort*" (concepts *n°*2 and 5): the score for velocity for seat 4 is not maximum, and (iii) "*Poor comfort*" concept (concept *n°*2, 4, and 6): the score for velocity for seats 2 and 4 is not maximum.

These three comfort classes can be directly read on Figure 4. Each class is given by one MV concept in the lattice and the order defined on the MV concepts also holds for the comfort classes : Concepts 3, 5 and 6 corresponding respectively to maximum, intermediate, and poor comfort classes. The colors linked to concept scores in Figures 4 and 3 allow to quickly identify the concepts corresponding to the most relevant design configurations and to extract ranges of variation of the corresponding design parameters. These extracted ranges are given in Table 3.

Table 3: Extracted ranges of the 13 comfort design problem parameters for different classes of comfort.

Parameter	Range	"Maximum comfort" range	"Intermediate comfort" range	"Poor comfort" range
Alpha_1 (°)	[-90, -80]	[-86.61, -83.05]	[-89.83, -80.56]	[-89.83, -80.56]
Alpha_2 (°)	[-100, -45]	[-96.65, -54.66]	[-96.65, -46.52]	[-96.65, -46.52]
Alpha_3 (°)	[-135, -90]	[-133.35, -100.3]	[-134.22, -91.59]	[-134.22, -91.59]
Alpha_4 (°)	[-120, -80]	[-105.77, -87.14]	[-105.77, -81.15]	[-105.77, -81.15]
Uair_1 (m/s)	[0.2, 0.7]	[0.30, 0.69]	[0.20, 0.69]	[0.20, 0.69]
Uair_2 (m/s)	[0.2, 0.7]	[0.38, 0.67]	[0.23, 0.67]	[0.23, 0.67]
Uair_3 (m/s)	[0.2, 0.7]	[0.39, 0.63]	[0.20, 0.63]	[0.20, 0.63]
Uair_4 (m/s)	[0.2, 0.7]	[0.24, 0.64]	[0.24, 0.68]	[0.24, 0.68]
Uair_In (m/s)	[0.6, 3]	[2.59, 2.82]	[1.68, 2.98]	[0.81, 2.98]
Tair_In ($°C$)	[22, 25]	[22.82, 23.45]	[22.71, 23.53]	[22.71, 24.65]
Tair_P ($°C$)	[22, 25]	[22.08, 22.88]	[22.08, 24.29]	[22.08, 24.74]
T_ext ($°C$)	[-65, -50]	[-64.84, -52.86]	[-64.97, -50.25]	[-64.97, -50.25]
Kappa_F (W/K)	[$1e^{-4}$, $4e^{-4}$]	[$1.03e^{-4}$, $1.28e^{-4}$]	[$1.03e^{-4}$, $1.99e^{-4}$]	[$1.03e^{-4}$, $1.99e^{-4}$]

5.4   Evaluating the Extracted Design Parameters' Ranges Through New Simulations

In order to evaluate the obtained results, we considered the extracted ranges of input parameters corresponding to the maximum comfort class for new simulations to check wether the output values of temperature and velocity belong to the same comfort class. We performed 12 new simulations for which input parameters take randomly chosen values in the ranges of the maximal comfort class previously extracted. All of the twelve simulations resulted in maximal comfort values for temperature and velocity mean values for each of the four seats. That is, in each seat, the mean value of temperature is between 22.5°C and 23.5°C and the mean value of velocity is less than 0.2. The obtained values are in the following ranges: T1: [22.57, 23.16], T2: [22.64, 23.30], T3: [22.84, 23.40], T4: [22.76, 23.29], V1: [0.013, 0.041], V2: [0.016, 0.062], V3: [0.001, 0.004], and V4: [0.148, 0.2].

The ranges of the input parameters for the new simulations extracted from this lattice are shown in Table 4 (column: New range).

Compared to the ranges previously obtained for the maximum comfort class (also given in Table 4, column: Maximum comfort range), the new ranges are almost the same as the maximum comfort ranges for all the input parameters. As the new simulations resulted in values of temperature and velocity in full compliance with the maximum comfort class values, this means that the simulations converge to the ranges obtained for the maximum comfort class. These ranges can then be confirmed by the system designer as one possible optimal solution for the multidimensional problem of passengers comfort in the aircraft cabin.

We proceeded in the same way to evaluate the extracted ranges of the intermediate comfort class. The twelve simulations performed for values of input parameters randomly chosen in the ranges corresponding to the intermediate comfort class have produced values of temperature in the interval [22.5,23.5]. However velocity values in seat 4 resulted in values in the interval [0.2,1] for eleven simulations which correspond to intermediate comfort. These results also confirm the ones previously obtained. In addition, input parameter ranges are included or equal to the ones obtained in the previous case which means that the simulations converge as in the case of maximum comfort class.

The evaluation of the extracted parameters ranges for the poor comfort class in the same way produced similar results and confirmed the convergence of the simulations to the solution extracted from the MV lattice given in Figure 4.

These results show the usefulness of the presented approach for supporting a system designer to improve and validate the choice for a design solution of a complex system based on simulation results. In addition, the genericity and the flexibility of SFCA formalism makes it possible to adapt the presented approach and apply it to similar problems.

6   Conclusion

In this paper we presented an approach based on conceptual structures to support complex system designers in the identification of relevant design configurations. The approach takes advantage of SFCA formalism to study the thermal comfort of 4 passengers in an aircraft cabin whose ventilation system is parametrized by 13 design parameters. The design problem takes into account 9 decision criteria defining the passengers comfort and energy consumption of the air ventilation system. A dataset of 100 randomly chosen simulated configurations is considered for the aircraft case study. The use of SFCA following a smart analysis strategy through the choice of appropriate similarity thresholds allows to directly deduce the ranges of values of input parameters which guarantee different levels of passengers comfort. In addition, an adapted visualisation of MV lattices delivers a tractable and easy way to read them easing the design and decision making process. The obtained results are then evaluated by new simulations which converged to the same solutions in terms of passengers comfort as well as in terms of input parameters ranges.

Table 4: Extracted ranges of the 13 comfort design problem parameters for the maximum comfort class and for the new simulations.

Parameter	"Maximum comfort" range	New range
Alpha_1 ($°$)	[-86.61, -83.05]	[-86.27, -83.30]
Alpha_2 ($°$)	[-96.65, -54.66]	[-95.38, -56.82]
Alpha_3 ($°$)	[-133.35, -100.3]	[-131.51, -103.58]
Alpha_4 ($°$)	[-105.77, -87.14]	[-103.08, -87.87]
Uair_1 (m/s)	[0.30, 0.69]	[0.33, 0.68]
Uair_2 (m/s)	[0.38, 0.67]	[0.39, 0.60]
Uair_3 (m/s)	[0.39, 0.63]	[0.39, 0.63]
Uair_4 (m/s)	[0.24, 0.64]	[0.26, 0.59]
Uair_In (m/s)	[2.59, 2.82]	[2.61, 2.82]
Tair_In ($°C$)	[22.82, 23.45]	[22.86, 23.42]
Tair_P ($°C$)	[22.08, 22.88]	[22.14, 22.88]
T_ext ($°C$)	[-64.84, -52.86]	[-64.27, -54.27]
Kappa_F (W/K)	[$1.03e^{-4}$, $1.28e^{-4}$]	[$1.07e^{-4}$, $1.27e^{-4}$]

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