ASSESSMENT OF DEPENDENCIES IN MECHATRONICS CONCEPTUAL DESIGN OF A QUADCOPTER DRONE USING LINGUISTIC FUZZY VARIABLES

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Abstract

The multi-disciplinary nature of Mechatronic Systems (MeSy) results in a highly complex design task, and it is believed that using an integrated approach to design would help reduce this complexity. However, integrated design is hard to implement due to the existing interactions between the components of MeSy. Some of these interactions are referred to as dependencies, and can affect the performance of MeSy while increasing the design task complexity. It is thus necessary to deal with them as early as possible. Although there are some methods to model dependencies, no methods exist to deal specifically with negative effect dependencies. Therefore, we propose a method that enables the identification and assess negative dependencies that exist within a mechatronic system. We first define negative dependencies between two components through four dimensions (affecting level, affected level, effect attenuation and functional closeness) and then assess these dimensions using fuzzy linguistic variables. We then demonstrate the effectiveness of the method by using a quadcopter drone as a case study which shows that it is possible to gain knowledge regarding potential design problems early on.

Keywords: Mechatronics, Case study, Integrated product development, Fuzzy logic, Decision making

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1 INTRODUCTION

Mechatronic systems are the result of integration of mechanical components, electronics and software, all aided by control algorithms. These systems are involved in many different industrial domains, notably in robotics and in the automotive and aerospace industries. Since mechatronic systems involve multiple aspects of engineering domains, it is of utmost importance to design the system concurrently while considering all of these interlacing aspects in order to achieve a near optimal product (Rzevski, 2003), hence avoiding the trap of having domain specific optimal subsystems that do not form an optimal whole when put together due to negative dependencies (Torry-Smith et al., 2012). This concurrent and collaborative approach have to be preferred over the traditional sequential design method (Rzevski, 2003). However, this approach is shown to be challenging to implement, especially due to the high number of dependencies between the system components (Mohebbi et al., 2014).

It is worth noting that a dependency is generally defined as the relationship that exists between two components when one affects the other. The affecting component is usually referred as the antecedent while the affected one is the dependent. By being able to identify, as early as possible, the various dependencies involved in a system design, it is possible to either avoid them, or mitigate their effects. Torry-Smith et al. (2014) proposes a classification method to help identify product related dependencies, which are dependencies that would exist between functions, means and properties. More specifically, Torry-Smith et al. (2014) identifies 13 different types of product related dependencies and provides a description for each of these dependencies along some methods to model them. One of the main identified dependencies are the adverse effect of means, which can be related to functions such as release heat or induce vibrations, and can be detrimental to the performance of the mechatronic device. However, those dependencies are difficult to identify as there exists a very limited set of tools, if not at all, that could be used for dealing with them at early design stages. Indeed, it is reported that undesired interaction between subsystems are usually unforeseeable and are found after building physical prototypes (D'Amelio and Tomiyama, 2007).

The late detection of negative adverse effects in the design stages can result in costly redesign loops of certain components, or even the entire system in some cases, which in turns lengthens the design process. This could cause increased costs and potential loss of technological edge in fast developing fields where short time-to-market is crucial. Some methods do exist to try to identify negative interactions in a qualitative way such as the Design Interference Detector (DID) methodology (D'Amelio et al., 2011; D'Amelio and Tomiyama, 2007), which consists of using qualitative physics to identify interactions. However DID requires a vast knowledge base in order to be used, especially in terms of knowledge about previous failures and features which might render the process computationally heavy. Although some qualitative methods exist, there is no method to assess adverse effects in a quantitative manner.

By being able to identify and quantify negative dependencies in a system, design engineers will have the opportunity to detect problems early on as well as assess their severity. Doing so would enable them to make better, more advised decisions as if there is a need to change or alter the concept, or a component, or if the various adverse effects can simply be overlooked.

In order to compensate for the lack of an efficient qualitative method for assessing dependencies, we propose to use linguistic fuzzy variables to describe negative effects in a mechatronic system. The use of linguistic variables will enable us to quantify the level of negative dependencies between the antecedent and the dependent and therefore support the design decision making process.

This paper proposes a method that allows for both modelling and assessing the adverse effects that could be present in a mechatronic system. We first present the main existing methods to deal with dependencies that have been traditionally used or recently introduced. We then present a new method to model and assess adverse effects in mechatronic systems. Finally, we demonstrate the use of our proposed method with a case study on a quadcopter drone design.

2 DEPENDENCY MODELLING

Dependencies are intrinsic to any system design, in particular mechatronic multi-domain systems, and can be related to many factors. It is important to state that in this paper we only deal with product related dependencies (Torry-Smith et al., 2014) and they will be referred to as simply dependencies. As mentioned previously, dependencies can exist between functions, means, and properties of mechatronic system. For instance, a dependency could exist between a function such as to provide power and the mean which would be the power source, such as a battery or a power pack. Furthermore, there could also be dependencies between the mean, such as a battery type, and a property such as the energy density. These dependencies influence the final product and hence have to be considered as early as possible in the design process. However, unfortunately engineers tend to discover them late in integration meetings or even miss them all together (Torry-Smith et al., 2014, 2015). To better understand and deal with the potential challenges that could be encountered, engineers will usually need to rely on dependency modelling tools.

Dependency modelling is a useful tool for design engineers since it allows them to understand the various relationships that exist between the different components of a system. Furthermore, it also enables them to detect future problems which could be related to negative effects of one component on another. Moreover, being able to model the dependencies can lead to being able to better manage them later on. Finally, a good modelling of dependencies can help understand the effect of design change propagation of one component on the other components of the system. Although there are different modelling tools that exist in order to carry out dependency modelling, one of the most widely used remains the Design Structure Matrix (DSM) (Browning, 2001; Steward, 1981).

DSM expresses the interactions/relationships of the various components of a system using a square matrix of dimension n; n being the number of components in the system. In order to express the relationship that exists between the antecedent i and the dependent j, a marker is inserted in the matrix at the location row = i, column = j. An example of a DSM is shown in Figure. 1(a). The DSM usually expresses components within a single engineering domain and thus can be extended to the Domain Mapping Matrix (DMM) which instead of having components from a single domain, the components are from two domains (e.g. mechanical and electrical) present in the system. Finally, using the DSM and DMM together it is possible to form a Multi-Domain Matrix (MDM) which enables us to get an overview of all the component/domain interactions of the mechatronic system and thus better manage the integration exercise during the design process.

	A	B	C	D
Element A			X	
Element B	X			X
Element C		X		X
Element D		X		

(a)

	D1	D2	D3	D4
Domain 1	DSM	DMM	DMM	DMM
Domain 2	DMM	DSM	DMM	DMM
Domain 3	DMM	DMM	DSM	DMM
Domain 4	DMM	DMM	DMM	DSM

(b)

Figure. 1. (a) Design Structure Matrix (b) Multi-Domain Matrix

DSMs are easy to use as they are a rather compact representation of information and can be accomplished on simple spreadsheet. However, their use is heavy on design time as they require a lot of involvement of the designer, or more often a team of engineering designers, as building the DSM would require the design team to go over all the possible relationships that could potentially exist between any pair of components. In order to reduce the required work during the dependency modelling, the research presented by Haddad (2015) proposes a framework that could be used in order to better identify the dependencies at early stages of design, it uses the notion of adverse effect of a function such as heat, vibration, or electric field. More specifically, it achieves this by identifying which functions generate an adverse effect (called the affecter) and which ones are affected by this effect (called the affected), it is therefore possible to create a dependency mapping through the use of if-then rule as follows:

If function 1 generates adverse effect A and function 2 is affected by adverse effect A then a dependency between function 1 and function 2 is created.

Using this approach, it is possible to only state which functions affect or are affected and the resulting set of rules generate automatically the dependencies. This greatly reduces the number of inputs required to find negative dependencies between system components. However, the method does not allow one to quantify the level of dependency (extent to which components are dependent to one-another) that exists within the mechatronic system.

Apart from the DSM and DSM-based methods, there is only a scarce amount, if not at all, of tools that can effectively be used to try to assess or quantify dependencies. Indeed, the assessment measures introduced in DSM are mainly based on designers own decision and expertise level. One method to help

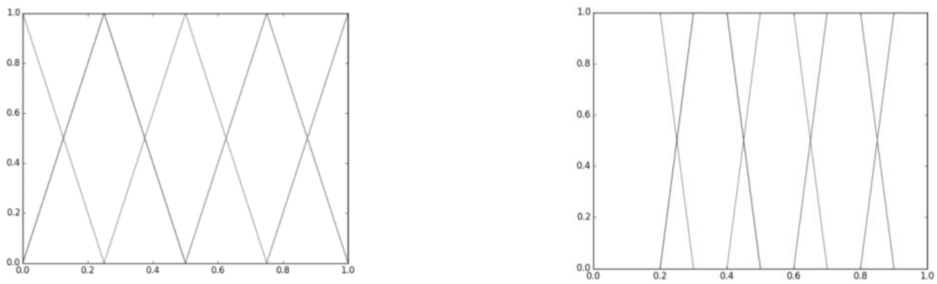
engineers to quantify the level of interaction between the components is proposed by Pimmler and Eppinger (1994) which consists of a 5 level scale representing if an interaction (spatial, energy, information, material) is detrimental, undesired, indifferent, beneficial or required. This scale combined with DSM provides a mean for clustering the components. However, this method again still requires a large number of inputs from the designers in order to rate the various interactions.
Although dependency modelling and assessment is essential to streamline the development of high-performance mechatronic devices, current methods are inefficient as too much emphasis relies on the experience of the engineers and error-prone human decision making. Furthermore, most of the existing methods require a high level of precise knowledge of the system to be designed which is often not even available at early design stages. Therefore, to deal with this imprecision we propose to exploit fuzzy-logic based fuzzy numbers. Fuzzy numbers will allow the possibility to capture the uncertainty in the assessments of the designers. More precisely, the fuzzy numbers will be represented by fuzzy linguistic variables that can better represent human thinking process (Chen and Ku, 2008) and thus could be used in dependency modelling and assessment.

3 LINGUISTIC FUZZY VARIABLES

Linguistic fuzzy variables have been widely used to quantify properties that are difficult to assess by using a linguistic scale of preference/performance. Indeed, these fuzzy numbers have been employed in Kansei engineering (Achiche and Ahmed-Kristensen, 2011; Chou, 2014) or to evaluate the appropriateness of alternatives (Chang and Chen, 1994). For more information, an extensive list of fuzzy linguistic scales and their use is provided by Chen and Ku (2008). Fuzzy linguistic variables are usually more intuitive to employ than single fuzzy numbers. Indeed, describing a phenomenon with words is closer to human reasoning than it is with using a single number.
Furthermore, by considering standard triangular/trapezoidal fuzzy membership functions, each components of the linguistic scale is associated to a triangular fuzzy number (TFN) or a trapezoidal fuzzy number (TrFN). This allows us to capture the uncertainty associated with the linguistic statement. Indeed, a TrFN has the form $\langle a,b,c,d \rangle$ where a,b,c,d are the vertices of the trapezoidal number with a being the left bound and d being the right bound. In the case of a TFN defined as $\langle a,b,c \rangle$, a,c will be the left and right bounds respectively. The uncertainty is captured by the bounds around the central values. An example of a linguistic scale is presented in Table 1 with their respective graphical representation in Figure. 2.

Table 1. 5 Level linguistic scales with TFN and TrFN values

Linguistic value	*Very low*	*Low*	*Medium*	*High*	*Very high*
TFN value	$\langle 0,0,0.25 \rangle$	$\langle 0,0.25,0.5 \rangle$	$\langle 0.25,0.5,0.75 \rangle$	$\langle 0.5,0.75,1 \rangle$	$\langle 0.75,1,1 \rangle$
TrFN value	$\langle 0,0,0.2,0.3 \rangle$	$\langle 0.2,0.3,0.4,0.5 \rangle$	$\langle 0.4,0.5,0.6,0.7 \rangle$	$\langle 0.6,0.7,0.8,0.9 \rangle$	$\langle 0.8,0.9,1,1 \rangle$



(a) (b)

Figure. 2. Graphical Representation of the 5 level scale for (a) TFN and (b) TrFN

Since linguistic fuzzy variable are represented by triangular/trapezoidal fuzzy membership function (numbers) they have various mathematical properties, with the most useful one in decision making being aggregation. One of the mainly used aggregation methods remains the arithmetic mean (AM) which is defined, as a general case, for n trapezoidal fuzzy number $\langle a_1, b_1, c_1, d_1 \rangle, ..., \langle a_n, b_n, c_n, d_n \rangle$ by Equation (1) (Klir and Folger, 1988).

$$\langle \bar{a}, \bar{b}, \bar{c}, \bar{d} \rangle = AM\left(\langle a_1, b_1, c_1, d_1 \rangle, ..., \langle a_n, b_n, c_n, d_n \rangle\right)$$
$$\text{with } \bar{a} = \frac{1}{n}\sum_1^n a_i,\ \bar{\mathrm{b}} = \frac{1}{n}\sum_1^n b_i,\ \bar{\mathrm{c}} = \frac{1}{n}\sum_1^n c_i,\ \bar{\mathrm{d}} = \frac{1}{n}\sum_1^n d_i \quad (1)$$

Although triangular/trapezoidal fuzzy numbers are used with linguistic variables, they are not intuitively comparable once aggregated and it is usually impossible to associate them with a linguistic term. However, it is possible to obtain a single value from these numbers though a defuzzification process. A method for defuzzification of TFN/TrFN results in finding the centroid of the resulting shape comprised between the lower and upper bounds. As a general case, for a trapezoidal fuzzy number, the centroid is given by Equation (2) (Allahviranloo and Saneifard, 2012).

$$x(A) = \frac{1}{3}[a + b + c + d - \frac{dc - ab}{(d + c) - (a + b)}] \quad (2)$$

By using linguistic variables, it is possible to facilitate the description of the dependencies present in a system. The method to do so is presented in the next section.

4 ADVERSE EFFECT DEPENDENCIES

4.1 Dimensions of Dependencies

As mentioned earlier, negative dependencies are detrimental to the performance of the system. These negative dependencies would usually be related to the adverse effect that a component might generate. Typically, the adverse effects that are considered are the Heat, Vibration, and Electromagnetic Fields (EMF) as they are physical effects that can be detected. We define a negative dependency as a function of 4 main properties:

1. Affecter Level (AR): the extent to which a component affects (or generates an adverse effect),
2. Affected Level (AD): the extent to which a component is affected,
3. Functional Closeness (FC): the extent to which two components have to be physically close in order to function properly (or the extent to which two components are to one-another) and,
4. Effect Attenuation (EA): the extent to which the adverse effect attenuates over the increase of distance.

It is worth noting that the engineers/designers need to identify these four parameters as early as possible in the design process. A way of achieving this would be through the use of the early system level representation of the concept. For instance, if it is required to assess the dependency related to heat between a battery and a motor, then it is known that a battery generates heat. However, motors are not necessarily required to be close to the power source in order to function properly and are only lowly affected by heat. Finally, heat effect level is known to reduce as distance increases.

For each of the previously mentioned dimensions, we can then associate a linguistic fuzzy variable to it. A formal description of each of the dimensions with a linguistic scale is given in Table 2.

Table 2. Proposed linguistic scale for describing the dimensions of a dependency

Affecter level (AR)	Extent to which affecter generates adverse effect				
Affected level (AD)	Extent to which affected is affected by adverse effect				
Functional Closeness (FC)	Extent to which components have to be close				
Effect Attenuation (EA)	Extent to which adverse effect attenuates over distance				
Linguistic variable	*Very low*	*Low*	*Medium*	*High*	*Very high*
TFN	$\langle 0, 0.1, 0.25 \rangle$	$\langle 0.15, 0.3, 0.45 \rangle$	$\langle 0.35, 0.5, 0.65 \rangle$	$\langle 0.55, 0.7, 0.85 \rangle$	$\langle 0.75, 0.9, 1 \rangle$

4.2 Assessing Dependencies Between Two Components

In order to form a single fuzzy number that represent a certain adverse effect relation between two components in a system, it is required to combine the various dimensions. The first step is to create a distance factor f_D related to the functional closeness and the effect attenuation. To do so, we take the max of FC and of the complement of EA which is defined by Equation (3).

$$f_D = \max(FC, \overline{EA}) \tag{3}$$

Where the complement of a fuzzy number $u(x)$ is defined by Equation (4).

$$\overline{u(x)} = 1 - u(x) \tag{4}$$

The hypothesis behind this first operation is that the further a component is from a highly attenuating source, the least it would be affected. Moreover, even if a component is located far from a lowly attenuating source, the felt effect would be high. This can be transcribed by taking the complement of EA. Once the distance factor is computed, it can be combined with the affecting and affecter level of the dependency through the arithmetic mean (AM) defined in Equation (5). Thus, the dependency of adverse effect k between component i and j, namely $d_{k,ij}$, can be calculated by Equation (5).

$$d_{k,ij} = AM(\mathrm{AR}_i, \mathrm{AD}_j, f_{D_{k,ji}}) \tag{5}$$

Finally, the last step in the dependency assessment process is to combine the various adverse effects in order to get a single value representing the total dependency from a component to another. It is proposed to add the defuzzified values (Equation (2)) of each adverse effect between two components in order to obtain a single value representing the total level of negative dependency between any two components. We propose to describe FC as being low or very low by default and only specify otherwise if they do have FC or for instance if the components are part of a bundle (such as in avionics) or that there is a compactness requirement for the system. By assuming a default value, it greatly reduces the number of inputs required in order to carry out the dependency assessment. Furthermore, we propose to describe EA for the three main adverse effects as it is given in Table 3. This assessment is based on the fact that vibration might propagate through the structure of the system. Furthermore, although both heat and EMF reduces following $1/r^2$ with r being the distance from the source, heat might be conducted by metal components but EMF could create a Faraday's cage with the structure and thus be isolated.

Table 3. Proposed Effect Attenuation Assessment

Effect	Linguistic Variable
Vibration	*Low*
Heat	*Medium*
EMF	*High*

4.3 Dependency Assessment Example

A simple example of the use of the method with four components {C1, C2, C3, C4} and two adverse effects {Heat, Vibration} is shown below. We also set that the default value for functional closeness is *low*. Furthermore, there is a possibility that a component affects itself (such as a computer that generates heat, but its functioning is impaired by heat) and hence we set the functional closeness of a component on itself to very high in this case.

Table 4. Example of Describing Components of a System

Component	Affecting	Affected
C1	Vibration - *High* Heat - *Medium*	Heat - *Low*
C2	Heat – *Low*	Vibration - *Medium*
C3	-	Heat -*Medium* Vibration-*High*
C4	Vibration – *Very High*	Vibration - *Very Low*

Using the information provided in Table 3 and Table 4, it is possible to use a simple coded script to search for combinations of type Affecting-Affected and use Equation (5) to compute the dependencies between the components. Doing so results in finding the DSM (with defuzzified values) of the various adverse effect as shown in Figure.3(a)-(b) and by combining them to find the overall DSM such as in Figure. 3(c).

	C1	C2	C3	C4
Component C1	0.50	. . . .	0.56	. . . .
Component C2	0.35	. . . .	0.47	. . . .
Component C3	. . . .	. . . .	. . . .	. . . .
Component C4	. . . .	. . . .	. . . .	. . . .

(a)

	C1	C2	C3	C4
Component C1	. . . .	0.63	0.70	0.31
Component C2	. . . .	. . . .	. . . .	. . . .
Component C3	. . . .	. . . .	. . . .	. . . .
Component C4	. . . .	0.67	0.75	0.35

(b)

	C1	C2	C3	C4
Component C1	0.50	0.63	1.26	0.31
Component C2	0.35	. . . .	0.47	. . . .
Component C3	. . . .	. . . .	. . . .	. . . .
Component C4	. . . .	0.67	0.75	0.35

(c)

Figure. 3. (a-c) DSM for heat, vibration, and combined

By employing the proposed method for assessing the dependency, it is possible to quickly detect potential problems in the system. For instance, a large dependency as there is between C1 and C3 might lead to a decision to redesign these components, or focus the effort on mitigating the effects. In comparison, the dependency between C2 and C1 should require less effort to deal with, or it might even be decided that it could be overlooked. Furthermore, it can be seen that the proposed method effectively reduces the number of inputs required in the dependency assessment. Indeed, for a system with n components, we are able to potentially reduce the order from $O\left(n^2\right)$ to $O\left(n\right)$ for a highly dependent and complex system. This decreased number of inputs is related to the fact that it is only required to state whether a component is affected by, and/or affecting an adverse effect which would result in inputting up to $2\times m\times n$ variables with m being the number of adverse effect considered (3 in this paper). Comparatively, when using the DSM to carry out the same dependency assessment, one would require to input all possible combinations of components affecting each other, thus resulting in $m\times n^2$ potential combinations. In the previous example, only 9 inputs enabled us to identify all 16 relationships of each adverse effect. Whereas, if the traditional DSM method was used, it would have required to go over all 16 potential dependencies. Thus, it is easy to see that for a system with a large number of components, the required inputs to assess dependencies drops rapidly.

5 CASE STUDY: DEPENDENCY ASSESSMENT OF A QUADROTOR DRONE

We now demonstrate the proposed methodology with a real-world case study which is a radio-controlled camera drone. The design specifications require the control of the drone to be based on user input, however the drone should be able of autonomous hovering. These specifications require incorporating sensors to control the position, attitude and altitude of the drone which could be achieved using a GPS, inertia sensor and a sonar respectively.

There exists a large amount of information available regarding the design of these drones. More specifically, De Silva et al. (2016) provides a description of the fundamental components and subsystems required for the proper functioning of a drone along the various effects that could affect the performance of these subsystems. We provide a summary of these fundamental components alongside the adverse effects associated to them and a linguistic assessment in Table 5. Furthermore, a model of the drone is provided in Figure 4.

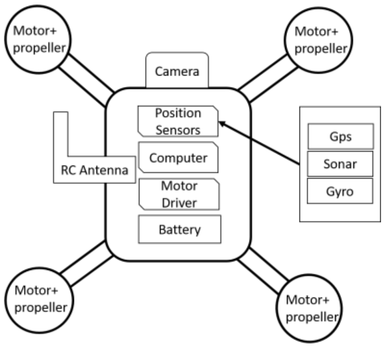


Figure. 4. Simplified model of the components of a quadcopter drone

Table 5. List of components and their related adverse effects

Component	ID	Function	Affecting	Affected
Actuator (motor + propeller)	A	Provide Motion	Vibration - *High* EMF - *Medium*	Vibration - *Medium*
Motor Driver	B	Modulate Power	Heat – *Low* EMF- *Medium*	Heat - *High* EMF- *High*
Gps	C	Position sensor	EMF – *Low*	Heat -*Low* EMF-*High*
Gyro	D	Attitude sensor	EMF- *Low*	Vibration - *Very High* Heat - *Low* EMF - *High*
Sonar	E	Altitude sensor	EMF- *Low*	Heat - *Low* EMF - *High*
Computer	F	Process Info + Control	Heat – *Medium* EMF – *Low*	Heat – *High* EMF- *Low*
Battery	G	Provide Power	Heat - *Very High* EMF - *Medium*	-
RC Antenna	H	Communication	-	EMF - *Medium*
Camera	I	Video Recording	EMF- *Low*	Vibration - *Medium* EMF - *High*

Quadcopter drones are usually designed to be compact in order to reduce the inertia of the system and thus to capture this standard requirement we set the default FC appropriately. A detailed description of the functional closeness of the components in the system is provided in Table 6.

Table 6. Functional Closeness (FC) of components

Components	Functional Closeness
Default	*Medium*
Gps-Sonar-Gyro	*Very High*
Actuator – All Others	*Very Low*
Camera – All Others	*Low*

Finally, by using our method as it was presented in section 4.2 and using Equation (5) with the information provided in Tables 3, 5 and 6, it is possible to obtain the DSM of the system for each of the adverse effect (Figure. 5 (a)-(c)), as well as the overall DSM (Figure. 5 (d)) .

	A	B	C	D	E	F	G	H	I
Component A	....	....	....	....	....	....	....	....	....
Component B	....	0.62	0.30	0.30	0.30	0.43	....	....	....
Component C	....	....	....	....	....	....	....	....	....
Component D	....	....	....	....	....	....	....	....	....
Component E	....	....	....	....	....	....	....	....	....
Component F	....	0.50	0.43	0.43	0.43	0.69	....	....	....
Component G	....	0.62	0.55	0.55	0.55	0.69	....	....	....
Component H	....	....	....	....	....	....	....	....	....
Component I	....	....	....	....	....	....	....	....	....

(a)

	A	B	C	D	E	F	G	H	I
Component A	....	....	....	....	....	....	....	....	....
Component B	....	0.62	0.30	0.30	0.30	0.43	....	....	....
Component C	....	....	....	....	....	....	....	....	....
Component D	....	....	....	....	....	....	....	....	....
Component E	....	....	....	....	....	....	....	....	....
Component F	....	0.50	0.43	0.43	0.43	0.69	....	....	....
Component G	....	0.62	0.55	0.55	0.55	0.69	....	....	....
Component H	....	....	....	....	....	....	....	....	....
Component I	....	....	....	....	....	....	....	....	....

(b)

	A	B	C	D	E	F	G	H	I
Component A	....	0.45	0.45	0.45	0.45	0.31	....	0.37	0.44
Component B	....	0.69	0.45	0.45	0.45	0.31	....	0.43	0.45
Component C	....	0.43	0.62	0.62	0.62	0.25	....	0.31	0.50
Component D	....	0.38	0.62	0.62	0.62	0.25	....	0.31	0.50
Component E	....	0.38	0.62	0.62	0.62	0.25	....	0.31	0.50
Component F	....	0.38	0.38	0.50	0.50	0.49	....	0.31	0.38
Component G	....	0.45	0.45	0.45	0.45	0.31	....	0.50	0.57
Component H	....	....	....	....	....	....	....	....	....
Component I	....	0.38	0.50	0.50	0.50	0.37	....	0.43	0.62

(c)

	A	B	C	D	E	F	G	H	I
Component A	0.69	0.45	0.45	1.01	0.45	0.31	....	0.37	0.88
Component B	....	1.31	0.75	0.75	0.75	0.74	....	0.43	0.45
Component C	....	0.43	0.62	0.62	0.62	0.25	....	0.31	0.50
Component D	....	0.38	0.62	0.62	0.62	0.25	....	0.31	0.50
Component E	....	0.38	0.62	0.62	0.62	0.25	....	0.31	0.50
Component F	....	0.88	0.81	0.93	0.93	1.18	....	0.31	0.38
Component G	....	1.07	1.00	1.00	1.00	1.00	....	0.50	0.57
Component H	....	....	....	....	....	....	....	....	....
Component I	....	0.38	0.50	0.50	0.50	0.37	....	0.43	0.62

(d)

Figure. 5. DSM for (a) Heat, (b) Vibration, (c) EMF, (d) Combined

By carrying out the dependency assessment method it is possible to identify the main adverse effects of the system which is the Electro-Magnetic Field. The result of the analysis is consistent with the information provided by De Silva et al. (2016) which states that it is usually one of the main concerns during the design of small scale UAV.

By using the dependency assessment method on the quadcopter drone design, it is possible to see that dependency modelling can be made faster. Indeed, only 34 inputs were required to analyze all 300 potential dependencies (3 adverse effects, 10 components resulting in 100 dependencies per adverse effects). Furthermore, it is possible to collect information that is in line with current knowledge of the subject. While, quadcopter drones are now a highly studied and commercialized system, so a wealth of information is already available online, our proposed method confirms that it could be used during the design of new systems where information is scarce. Thus the method could potentially detect and quantify the extent to which negative dependencies are present in the system in a much faster way than what would typically be required by multiple testing. Furthermore, it is also possible to see that the method effectively reduces the involvement of the designer as it relies less on knowledge of the system which would be obtained from experience, but more on general knowledge of components which can be obtained online, from books or catalogs, or the traditional integration meetings.

6 CONCLUSION

In this work, a new method for assessing and modelling negative dependencies in a system was proposed. We proposed to define a dependency through four dimensions (Affecter Level, Affected Level, Functional Closeness and Effect Attenuation) and describe these dimensions using fuzzy linguistic variables. The proposed method effectively reduces the number of inputs required for identifying dependencies as well as enabling engineers to understand the extent to which to components in a system are dependent. We showed that it was possible to express current knowledge on widely a widely studied design case, and hence the method could be employed to identify dependencies with unknown systems. Doing so will greatly reduce the design process time and thus enable faster time-to-market which will be beneficial in highly competitive fields. Furthermore by employing fuzzy linguistic variables, the knowledge required to make the assessment can be transferred to new designs as it would not be possible to have exact understanding of the effects of one component to another. Moreover, fuzzy linguistic variables have the ability to capture the difference in perception between different designers and thus the final assessment might be similar even though intermediary assessments might not be.

Even though we proposed a method that enables to detect and quantify negative dependencies early in the design process, there is still work that remains to be carried out in order to be able to identify all of the product related dependencies. Doing so will enable us to increase the quality and reliability of mechatronic devices while reducing their cost. Furthermore, there is a need to use the knowledge gained in dependency modelling and assessment during the decision making process during the conceptual stage as doing so will allow us to select concepts that would potentially require less efforts to mitigate these dependencies.

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