



A Method for Assessing the Ability of Complex Engineered Systems under Uncertainty

Jafar Gheidar-Kheljani*, Mohammad Hossein Karimi Gavareshki, Malek Tahoori

Management & Industrial Engineering Department, Malek-Ashtar University of Technology, Tehran, Iran

ABSTRACT: Engineered systems are man-made systems created to deliver value/service to stakeholders. Many engineered systems should be operated for long period of times within unpredictable and dynamic conditions. Uncertainty can affect system output and its value/service delivery through different ways such as shifts in stakeholder needs and perturbations. It is important for end users to ensure that the system is operable and reliable in unknown environment. Assessing system capability and its ability to do missions under uncertainty conditions is still an important problem for end users. Non-functional properties such as flexibility and changeability are presented and formulated as a response to decrease the impact of dynamic complexities on system value/service delivery. In this paper viability as a good criterion is selected to measure system capability under uncertainty and a 7-step method is developed to measure it. The proposed method has three characteristics: describing the uncertainty in operational environment, analyzing how the uncertainty will affect functional and physical characteristics of the system and finally representing regions in the system architecture that are mostly impacted by operational uncertainties. Design Structure Matrix (DSM) is used to represent relationships between system properties and uncertain scenarios. Finally, an example is presented to show the application of the method.

Review History:

Received: Jun. 22, 2018

Revised: Nov. 29, 2019

Accepted: Dec. 01, 2019

Available Online: Jun. 15, 2020

Keywords:

Complex Engineered Systems
(CES)

Design Structure Matrix (DSM),
Non-Functional Requirements
(NFRs)

Uncertainty

Viability.

1- INTRODUCTION

Engineered systems are artificial systems designed to deliver value to its stakeholders [4]. The value depends on what the system is, what the system does, and contextual factors (e.g., the physical environment that surrounds the system, available resources, or stakeholder expectations) [22]. If anything does not change, then an engineered system that is providing adequate value to its stakeholders will continue to do so. However, it is expected that many engineered systems to operate for long period of times within uncertain conditions. It is not good enough for most complex systems to only “work” for a short period of time and under one specific context. Rather, stakeholders require that their systems work properly over a long period of time and variety of contexts. Thus, the issue for modern system architects is to not only design feasible systems, but also ones that will exist through long periods of time and possibly varying contexts.

Complex systems generally operate in dynamic and uncertain environment. System designers should design systems which continue providing acceptable value to their stakeholders in different situations. Various system properties or “-ilities” have been defined that may help traditional systems provide value to stakeholders in spite of change [4]. Regarding system parameter, outcome parameter and

*Corresponding author’s email: kheljani@mut.ac.ir

perturbation type, some properties such as changeability and versatility [1], survivability [2] and robustness [3] are introduced to increase the system abilities at unpredictable conditions. Fig.1 shows the applicability of every property in different situations. For example, a system is said to be versatile if without changing the system parameters, it can provide an output which has not designed to provide it [4]. Mekdeci [22] defines viability as the likelihood that an engineered system will provide acceptable value to its stakeholders over its life era. He defines era as both the expected time the system needs to last, as well as a sequence of epochs that it is expected to encounter. Consequently, if an engineered system provides acceptable value to its stakeholders over its life era, it is called viable. He has not introduced a way to quantify it. He says “although this research does not attempt to define metrics for viability, an engineered system can be more or less viable than another system, or to itself if something changes, since viability is a likelihood.” In this paper a 7-Step method is developed to measure viability of a system. The rest of the paper is structured as follows: section 2 reviews some studies about increasing a system ability to do its function at an ambiguous environment. A brief description on DSM (Design Structure Matrix) is presented in section 3. Section 4 describes a methodology to quantify viability as an NFR (Non-Functional Requirement) under uncertainty. In section 5, as



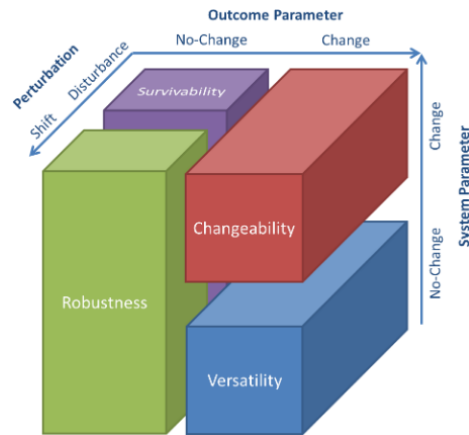


Fig. 1. Applicability of each property in different situations [21]

Table 1. Traceability measurement question Likert scale [7].

Descriptor	Measurement criteria
None	No objective quality evidence is present
Limited	Limited objective quality evidence is present
Nominal	Nominal objective quality evidence is present
Wide	Wide objective quality evidence is present
Extensive	Extensive objective quality evidence is present

an example, the model is applied on a satellite to demonstrate its application, and finally in section 6, conclusions and some comments for future studies are presented.

2- LITERATURE REVIEW

2.1. Review of NFRs definitions and assessment methods

In every current requirements classification, a distinction between requirements concerning the functionality of a system and other requirements exists [24]. One of the most easily understood tasks during any systems design endeavor is defining system functional requirements [7]. The functional requirements are a direct extension of the stakeholder’s purpose for a system and the goals and objectives that satisfy them. In addition to the obvious features and functions that you will provide in your system, there are other requirements that don’t actually DO anything, but are important characteristics nevertheless. These are called “non-functional requirements” or sometimes “quality attributes”. Other terms for non-functional requirements are “qualities”, “quality goals”, “quality of service requirements”, “constraints”, “non-behavioral requirements” or “technical requirements”. Informally these are sometimes called the “-ilities”, from attributes like stability and portability [23]. The following definitions are examples of “-ilities”:Survivability: Eillison [5] defines survivability as the capability of the system to achieve its requirements or goals, in a timely manner, in the presence of attacks, failures or accidents. The ability of systems to decrease the effects of contextual changes on value delivery is another definition of survivability [6].

Adams [7] has used the question “Does the system show

the ability to keep desired characteristics despite fluctuations as a result of internal changes and its environment?”. The answers to the question will be contained in a 5 point-Likert scale (Table 1) for measuring survivability.

Robustness: Robustness is another “-ility” that is closely related to survivability. The Oxford dictionary [8] defines system robustness as ability to withstand or overcome diverse conditions. According to Beesemeyer [21] proposition, robustness is the ability of systems to maintaining desired output despite of change in the system or its context. Like survivability, the measure of robustness can be obtained using a measurement question and the Likert scale which is proposed in Table 1. The related question is: “Does the system demonstrate the ability to maintain a desired characteristic despite fluctuations caused by either internal changes or its environment?” [7].

Changeability and Versatility: according to Westrum’s study [1], versatility of a system is providing an output that was not designed to do it, with no changes in parameters of the system. Also a system is known as changeable, if the system parameters can be changed for achievement of new outputs. Adams [7] has proposed four-level structural map for measuring changeability (Table 2).

Related measurements questions for changeability described in Table 3:

Table 1. has been used by Adams [7] for quantification of changeability measurement questions and then changeability value calculated as the sum of Ch_{adapt} , Ch_{flex} , Ch_{modif} and Ch_{robust} .

Viability: viability is the likelihood that an engineered system will provide acceptable value to its stakeholders, over

Table 2. Four level structural map for measuring changeability [7].

Level	Role
Concern	System adaption
Attribute	Changeability
Metric	System changeability
Measurable characteristic	Changeability of (1) adaptability, (2) flexibility, (3) modifiability, and (4) robustness

Table 3. Measurement questions for changeability [7].

Level	Role
Ch _{adapt}	Is the system able to adapt itself as a result of states changes caused by internal impetus?
Ch _{flex}	Is the system flexible enough to change as a result of state changes caused by external environmental impetus?
Ch _{modif}	Can the system be modified as a result of changes in the environment, requirements or functional specification?
Ch _{robust}	Can the system’s parameters remain “constant” in spite of system internal or external environmental changes?

Table 4. Measurement questions for Viability [7].

Level	Role
V _{under}	Can a person comprehend any portion of a system without difficulty?
V _{use}	What is the degree of effort required to learn, interpret, and effectively and efficiently operate a system?
V _{robust}	Does the system demonstrate the ability to maintain a desired characteristic despite fluctuations caused by either internal changes or its environment?
V _{surviv}	Does the system demonstrate the ability to continue to operate in the face of attacks or accidental failures or errors?

its life era [4]. Based on Mekdeci’s research [4] important concepts about viability are as follows:

Viability is subjective; whether a system is viable or not, is determined by how well the outputs of the system are likely to satisfy stakeholder needs.

Viability is dynamic: viability is a prediction about whether the system will provide acceptable value to its stakeholders over its life era. What constitutes the life era is a prediction made by the stakeholders at the time viability is assessed.

Viability is Relative: a system can be relatively viable compared to another system or to itself if something changes, since viability is probabilistic. The more likely that a system will provide acceptable value to its stakeholders over its life era, the more viable it is.

Based on Viability definition and its advantages against other NFRs, as it covers all of mentioned situation parameters, this non-functional property is selected to quantify system’s ability under uncertainty. Adams [7] has used the following measurement questions, as it is illustrated in Table 4, for measuring the systems’ viability.

$$V = V_{under} + V_{use} + V_{robust} + V_{surviv} \quad (1)$$

He expanded Equation (1) for measuring the viability of a system.

2.2. Review on designing NFRs in complex engineered systems (CES)

There are many attempts for designing NFRs in complex

engineered systems and assessing these “-ilities” in the face of uncertainty. Generally, researchers take 8 steps to design non-functional requirements in complex systems which is organized as follows [10]–[12]: Step 1 is determining value proposition and constraints. This step is very similar to problem scope definition [13]. Step 2 mainly discusses identification of potential perturbations that system may confront. Perturbations are subdivided into “shifts in context and/or needs”, and “disturbances”, which are finite/short duration changes of a system’s design, context, or needs that could affect value delivery [9]. Perturbation taxonomy that can help identifying the ways in which the system may fail to deliver value, is the main output of this step [14]. Step 3 is identification of the “-ilities” to promote the desired long-term behavior of them. The main activities for this step are: gathering direct and implied “-illity” requests from stakeholders, tracing perturbations to “-ilities” from the list of perturbations which diagnosed in step 2, finalizing a list of potential useful “-ilities”, saying mission needs and constraints which should put forward into analysis and be used to choose best architecture. Step 4 generates high-level concepts for CES architectures. It consists of a brainstorming session to come up with new constituent systems, as well as formulating various CES concept-of-operations. The main tasks of this step are: definition of high-level architecture concepts, generation of candidate CES forms [14], conducting design-value mapping qualitative assessment of the potential CES concepts’ fulfilment of stakeholders’ needs [15], finalizing the design space, and recording all assumptions made. Step

Table 5. Proposed “-illity” metrics for trade-offs within architectures [10]

“-illity”	Metrics	Stand for	Definition
Robustness	NPT	Normalized Pareto Trace	% epochs for which design is Pareto efficient in utility/cost
	fNPT	Fuzzy Normalized Pareto Trace	Above, with margin from Pareto front allowed
	eNPT	Effective Normalized Pareto Trace	Above, considering the design’s end state after transitioning
Changeability	efNPT	Effective Fuzzy Normalized Pareto Trace	
	FPS	Fuzzy Pareto Shift	Difference in FPN before and after transition
Survivability	FOD	Filtered Out Degree	Above, considering only arcs below a chosen cost threshold
Affordability	TAUL	Time-weighted Average Utility Loss	Integral of utility loss over time
	-	Accumulated Utility v. Discounted Cost	Lifecycle cost benefit

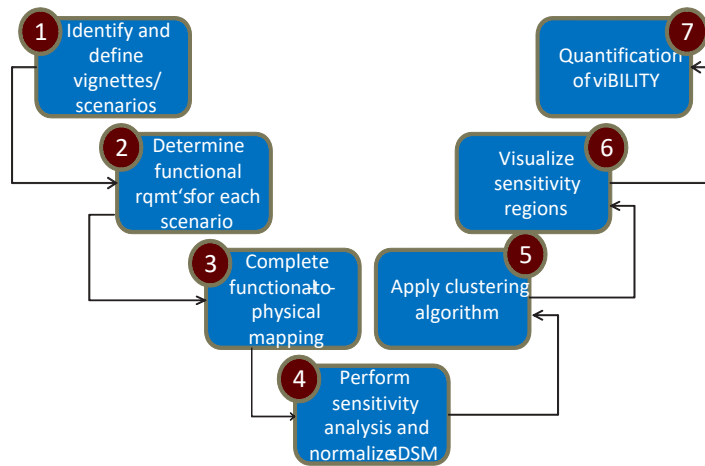


Fig. 2. 7-step model for assessing the viability

5 generates options resulting in the desired “-ilities” when added to system architecture [16]. This process consists of tracing perturbations identified in step 2 to the design variables and attribute list to estimate which design variables and attributes are impacted by changes [10]. After generating a comprehensive list of options, the next task is evaluating and comparing them to select the final list of options to consider. Some metrics to evaluate options are number of Uses, cost, perturbation coverage and optionability [17]. Using evaluation, a final list of options for consideration is obtained. Step 6 evaluates various CES architectures alternatives in the terms of different metrics, including value metrics (i.e. attributes and costs) and “-illity” metrics [14]. Step 7 develops and defines trade-offs within various CES architectures [18]. Some “-illity” metrics which can be used in this step are presented in [10]. Alternatives that perform well in “-illity” metrics can be identified to be traded with alternatives which perform well in other metrics, such as cost or utility. Step 8 involves final selection of architecture and design using the analysis results taken in step 7.

2.3. Literature review conclusion

As the consequence of literature review, viability has been selected as the criterion for assessing a CES ability under uncertainty because of following reasons:

- 1) There are number of non-functional requirements with

complex interrelationships. For reduction of ambiguities in calculation, it should be concentrate on a single criterion.

- 2) Against the other NFRs, viability is independent from 3 parameters (i.e. system parameter, outcome parameter and perturbation type) and covers all of them.

- 3) Advantage of viability such as dynamism etc. Although, no mathematical model was found on quantification of viability, it is better to develop the model in the way that the other researchers proposed for designing NFRs in complex engineered systems. The proposed model is developed based on Ricci’s conceptual model [10].

3- METHODOLOGY

System decomposition is the first step in evaluating the viability of a complex engineered system. Decomposition is breaking a system into known subsystems, it is important to define relationships between the subsystems and external inputs and outputs and their impact on the system [19]. DSM can be used for modeling how change propagates through a design, thus enabling DSM as a tool for describing the design under future uncertainty. Mapping functional requirements onto design variables, and studying how the functional requirements may change, change-sensitive design variables can be identified [25].

In this section a 7-step model is developed for quantifying complex system abilities under uncertainty. Fig.3 shows a

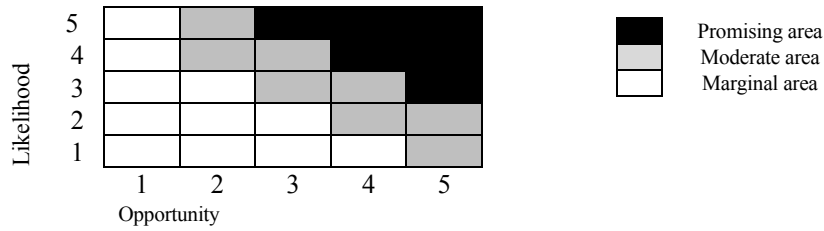


Fig. 3. Likelihood and consequence of each scenario

	Attributes					Design variables			
	a ₁	a ₂	a ₃	...	a _n	x ₁	x ₂	...	x _n
a ₁									
a ₂									
a ₃									
...									
a _n									
x ₁									
x ₂									
...									
x _n									

Fig. 4. A sample DSM

brief review of the model.

Step 1: The system’s operational environment is uncertain and unpredictable. To deal with that, designer of a system contrives some options. In this step a series of scenarios are provided, a scenario is defined by considering variation of missions and operational tasks. In each scenario different functions of a system are required to operate. S is a set of scenarios and s_i denotes ith scenario. $S = \{s_1, s_2, \dots\}$

To analyze the impact of each scenario on system architecture, scenarios must be prioritized. To do that, a 5*5 matrix (Fig. 4) used to present the likelihood and opportunity of each scenario. This research recognizes that high uncertainty also presents an opportunity to design systems that can flexibly respond to changing requirements and capture additional value throughout the design life. Risk is a level of threat due to potential problems, where knowledge of the risk is an opportunity to avoid a consequence of occurrence. Scenario Likelihood is the state of being probable or chance of a scenario occurring. A basic rubric based on Pierce research [12] is used to assist the collaborative effort of scoring each scenario when only limited types of information are available. Table 6 and 7 represent criteria for scoring the scenarios. Finally, in this step each scenario’s score is calculated as (2):

$$S_{sc}^i = S_{likelihood}^i * S_{opportunity}^i \tag{2}$$

Step 2: A functional analysis of the system is required to define those additional functions are needed to accomplish the scenarios. Functions are discrete actions of people or things necessary to perform the mission. This step is related to the developed scenarios and the system architecture. Subsets of the system functions that affect high level performance characteristics could be consolidated by defining system attributes. Each operational scenario needed some changes to one or more system attributes in order to respond to the new functional requirements. The attributes were used to represent the set of functional requirements providing a desired performance. Functional requirements and their relation with system attributes can be represented as (3):

$$\{FR_1^i, FR_2^i, \dots\} \in a_i \tag{3}$$

FR₁ⁱ, FR₂ⁱ and a_i denote “the first functional requirement of ith attribute”, “the second functional requirement of ith attribute” and “ith attribute” respectively.

Step 3: This step translates the functional requirements into physical parameters and/or design variables. For this objective, DSM technique is used to represent the system, its interfaces, and the intensity of its relationships. The relationship between endogenous and exogenous variables is explored in this step as a mean to understand how each scenario-generated functional requirement affects the physical design variables.

Table 6. Likelihood parameters

Probability	Stakeholder Environment	Operational environment	Design life
0-20%	Singular stakeholder	Well defined, predictable	Very short
20-40%	Consolidated stakeholder	Consistently defined	Short
40-60%	Centralized stakeholders	Some uncertainty	Moderate
60-80%	Decentralized stakeholders	High uncertainty	Long
80-100%	Highly decentralized stakeholders	Complex interconnected	Very long

Table 7. Opportunity parameters

Score	Performance	System value/ utility	Strategic
1	Minimal performance	Low cost/ high turnover	Minimal strategic importance
2	Small performance	Relatively low cost, comparative turnover	Limited strategic performance
3	Moderate performance	Moderate cost/ evolvable technology churn	Some strategic importance
4	High performance	High cost/ high value/ strategic significance	Very desirable component of larger operational context
5	Very high performance	Very high cost/ high value/ highly unprecedented	Necessary component of larger operational context

Fig. 5 shows a DSM for a system with k design variables and n attributes, a square matrix with k+n rows and columns. It's important to note that each attribute can also be expressed as a set of its constituent decomposed functional requirements.

Step 4: The system should be viable in regions of its architecture that are most sensitive to changes in functional requirements. So the objective of this step is to identify variables which are more sensitive to changes in the operational demands. A sensitive-DSM (sDSM) has been used to find sensitive regions in the architecture, in which the entry ij represented the normalized sensitivity of the parameter i to changes in the parameter j. For the design vector "X" the sDSM is a square matrix with k rows and columns, whose normalized entry ij represents the percent change in variable i caused by a percent change in variable j. X^* is desired design vector.

$$X = \{x_1, x_2, \dots, x_k\} \quad (4)$$

$$X^* = \{x_1^*, x_2^*, \dots, x_k^*\} \quad (5)$$

x_i and x_i^* denote "ith design variable" and "ith desired design variable" respectively.

$$sDSM(i, j) = \left(\frac{dx_i^*}{dx_j^*} \right) \left(\frac{x_i^*}{x_j^*} \right) \quad (6)$$

sDSM(i, j) and dx_i^* stand for "entry ij of a sDSM" and "value of change in ith design variable" respectively.

$$sDSM(i, j) = \left(\frac{dx_i^*}{da_j} \right) \left(\frac{a_j}{x_i^*} \right) \quad (7)$$

Each design variable is affected directly from the change in functional requirement, or indirectly from a propagated

change in another design element. This consideration is expressed as follow:

$$\Delta x_i = \sum_{j=1}^n \frac{\delta x_i^*}{\delta a_j^*} \Delta a_j^* + \sum_{j=1}^k \frac{\delta x_i^*}{\delta x_j^*} \Delta x_j^* \quad (8)$$

Equation (8) states that the required change in x_i is a cumulative change caused by all the functional requirements and other design elements to which x_i is sensitive in the neighborhood of x_i^* .

Step 5: By complete filling of DSM, clustering algorithm is used to consolidate physical design elements that are highly responsive to the changes imposed by future used cases or scenarios. There is a wide range of clustering algorithms, a sample of which can be found in Bartolomei [11] and Thebeau [20]. In this case, the clustering method which proposed by Thebeau [20] is selected for clustering the generated sDSM.

Step 6: this step combines the Likelihood-Opportunity (L_O) scores which are derived from Step 1 with the design sensitivity information derived from Step 4, it is shown in Fig.6. In this figure, for each (i,j), i denotes Sensitivity value and j denotes (L_O) value. This step provides insight into the regions in the CES architecture where changed or new functional requirements has most effects.

Step 7: At the final step, quantification of viability based on sensitivity regions can be done. Based on the generated matrix in step 6, viability (V) can be calculated by equation 9. CSRV is equal to sum of "L-O" * "sensitivity number", z is number of elements and MSRV is equal to sum of "maximum value of (L_O)" * "maximum sensitivity value" for all occupied (sensitive) cells and can be obtained by equations 10 and 11.

$$V = 1 - \frac{CSRV}{MSRV} \quad (9)$$

	1	2	3	4	5	6	7	8	9	10
1			5,2							
2	1,3									4,2
3		2,1								4,1
4					2,1					4,3
5				2,3		1,3				
6										
7										
8			4,3	5,2					5,1	
9				3,1				5,3		
10										

Fig. 6. Combination of L_O and DSM matrix

Table 8. Represented scenarios and their related scoring.

Scenario	Scenario. Description	Likelihood	Opportu
1	Desire for better image resolution	5	5
2	Desire for better image quality	1	2
3	Need for increased swath	3	4
4	Need for increased imaging time per orbit	3	3

	5					S1 promising
likelihood	4		moderate			
	3			S4	S3	
	2	marginal				
	1		S2			
		1	2	3	4	5
		opportunity				

Fig. 7. Developed scenarios scoring matrix.

$$CSR\ V = \sum_{i=1}^z \sum_{j=1}^z (L_{-} - O)_{ij} * S_{ij} \tag{10}$$

$$MSRV = \max L - O(L_{-} O)_{-} \max * S_{-} \max \max S * \# \text{ sensitive elements} \tag{11}$$

4- ILLUSTRATIVE EXAMPLE

The applicability of the proposed model has been checked using 5 different assumed Synthetic Aperture Radar (SAR) satellite architecture as a complex engineered system. In this section one of these experiments is represented as an illustrative example.

4.1. Explanation of illustrative example

In Step 1, different mission scenarios are developed to understand and define uncertainty in the operational environment. Then represented scenarios are scored based on

Table 6 and Table 7 and results shown in Table 8 and Fig. 7.

Then additional functions required for accomplishing the mission scenarios are identified. These functional requirements are listed in Table 9.

Subsets of the system functions that affect high level performance characteristics could be consolidated by defining system attributes. Each operational scenario needed some changes to one or more system attributes in order to respond to the new functional requirements. To simplicity, the functional requirements for each scenario are replaced by the affected system attribute, are shown in Table 11.

In step 3 system attributes have been mapped to design variables and are shown in Table 10. Then the design structure matrix is populated using a sample SAR block diagram and the expanded DSM model is shown in Fig. 8.

Table 9. Functional requirements for each scenario

Scenario Number	Related functional requirement(s)
1	[FR.1.1] spacecraft should be capable of maneuver for spotlight imaging mode. [FR.1.2] power subsystem should supply enough electrical power for increasing spacecraft image resolution. [FR.1.3] system should have enough memory to support increased imaging resolution
3	[FR.3.1] Antenna beam should be increased for desired swath [FR.3.2] power subsystem should supply enough electrical power for increased antenna beam
4	[FR.4.1] communication data rate should support increased imaging raw data transmission [FR.4.2] Ground segment equipment's should support high data rate

Table 11. Mapping mission scenarios to system attributes

senario	FR	attribute	KPP
1	FR.1.1, FR.1.2, FR.1.3	a1	resolution Range
2		a2	IRF
3	FR.4.1, FR.4.2	a3	timeliness
4		a4	GEO location
	FR.3.1, FR.3.2	a5	swath

Table 12. Mapping system attributes to design parameters

Attribute	Design parameters
Resolution range	Bandwidth, incidence angle ,power and data Rate
Resolution azimuth	Antenna length and minimum PRF
IRF	PSLR, ISLR and antenna gain
Swath	Incidence angle, antenna width and height
Timeliness	Revisit time, altitude, inclination, ground station access, downlink rate, antenna type and antenna gain
GEO location	Pointing accuracy

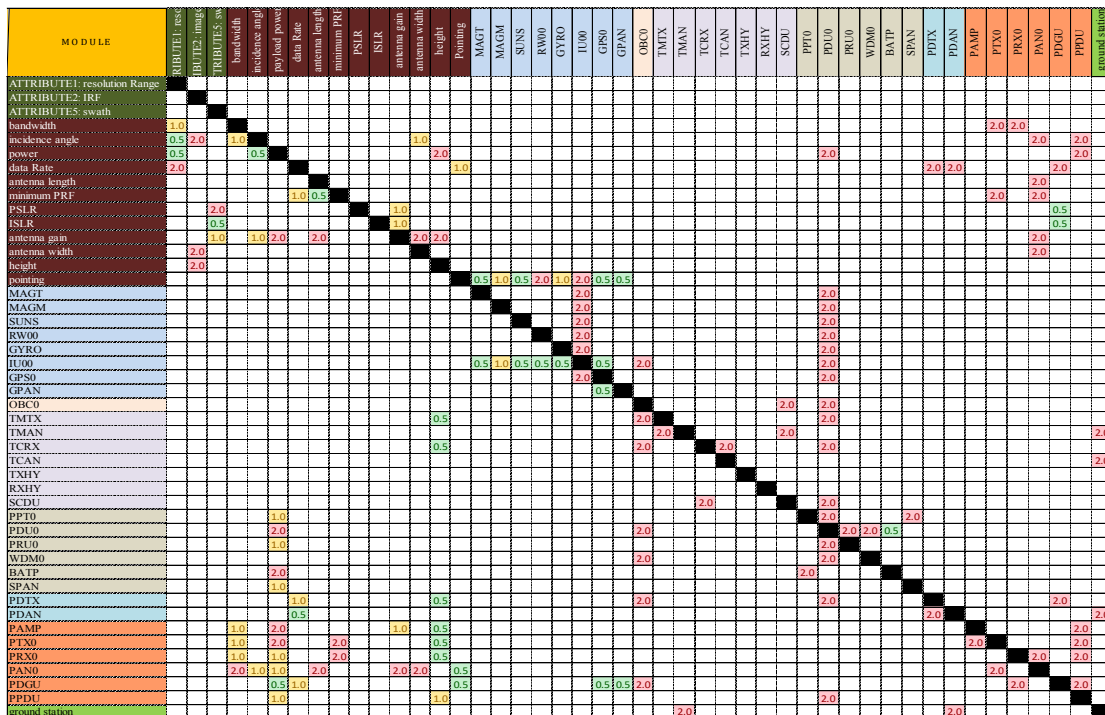


Fig. 8. sDSM matrix for designed SAR system.

Table 13. Sensitivity analysis for resolution range

Design parameter/ attribute	Design parameter value		Resolution range		Priority
	Max	Min	Max	Min	
Bandwidth (mhz)	30	8	15	56	2.0
Incidence angle (degree)	30	20	45	66	4.0
Power(Watt)	200	100	32	64	3.0
Data Rate(Mbps)	300	100	30	90	1.0

Table 14. Sensitivity analysis for swath width

Design parameter/ attribute	Design parameter value		Swath width		Priority
	Max	Min	Max	Min	
Incidence angle (deg)	30	20	25	20	1.0
Antenna width (m)	1.1	0.9	25	20	1.0
Height (Km)	500	400	22.7	18	2.0

Table 15. Sensitivity analysis for impulse response function

Design parameter/ attribute	Design parameter value		Impulse response function		Priority
	Max	Min	Max	Min	
PSLR (dB)	-6.3876	-6.775	-119.4	-121.4	2.0
ISLR (dB)	-9.3079	-9.9533	-121.4	-122.4	3.0
Gain (dB)	41	38	-121.4	-124.4	1.0

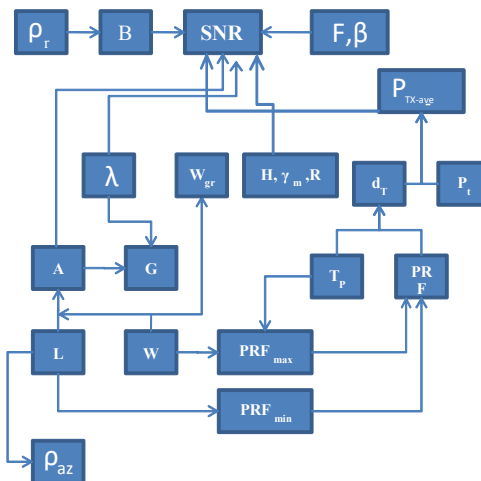


Fig. 9. Relationships between SAR parameters

To achieve the results of the expanded DSM, the implementation of step 4 and step 3 have been done simultaneously. A sensitivity analysis is performed to quantify the extent to which the system design variables must change in order to accommodate the changing requirements. As the SAR system model is large and the relationships are very complex, only three attributes related to the SAR payload have been chosen for the rest of analysis (i.e. Scenario 1, scenario 2 and scenario 3). Attributes are modeled using physical and mathematical relationships related to system parameters. These relationships are presented in Fig.10 and simulated using Equation 9. The results of sensitivity analysis are presented in Tables 12, 13 and 14.

Going down the list of design variables, the top is assigned

the most sensitive value of 2, while those at the bottom of the list are assigned to bin of value 0.5. Then sensitivity value is propagated through the DSM three tiers/levels. In step 5 the s-DSM has been clustered based on Thebeau proposed model [20]. The resulting clustered s-DSM displayed in Fig.10 contains 10 clusters of which cluster 4 and 5 are sensitive regions to the mission scenarios. As cluster 9 has no design parameter and subsequently no physical element, based on assumed system architecture it can be inferred that scenario 3 has no effect on system parameters and the swath can be changed without changing in system physical parameters. Finally, in steps 6 and 7, by combining the Likelihood-Opportunity scores derived from Step 1 with the design sensitivity information derived from Step 4 on the clustered

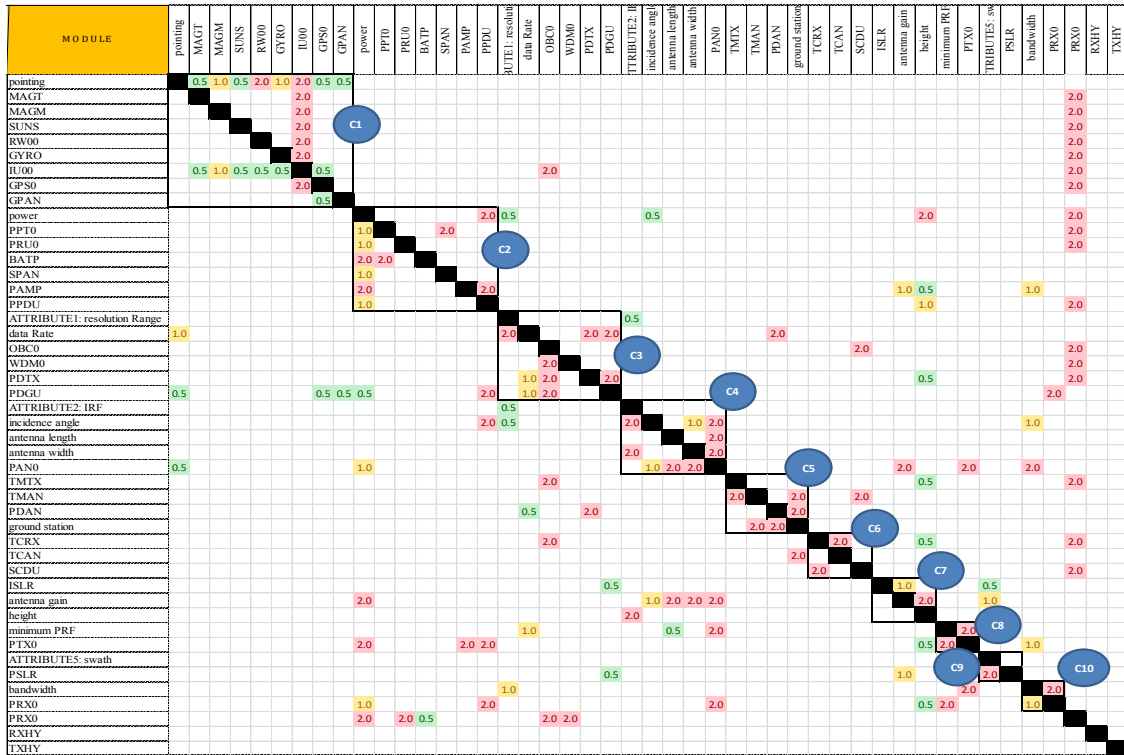


Fig. 10. Clustered sDSM for designed SAR system

Table 16. Advantages of the proposed model against other quantification models

Parameter/ model	Quantification models	This method
Levels of modeling	Two levels	Three levels
Analyzing of uncertainty	No	Yes
Change impacts	Yes	Yes
Change occurrence probability	Yes	Yes
Change propagation (direct and/ or indirect)	Yes	Yes

s-DSM matrix and using Equation 10, the Viability of system is 0.47. This value for viability parameter illustrated that the system is not very powerful under uncertainty and engineers should have more works on the optimization of system design so that the V parameter increases as possible. In the process of accomplishing illustrative example, each step of the process (inputs, procedures and outputs) has been checked and confirmed by experts for its logicity.

4.2. Model goodness and validation

Based on the following reasons can be declared that the proposed model in this article has more advantages for assessing the ability of complex engineered systems under uncertainty among the others in literature. The first reason is related to advantages of viability as a unique criterion for propose of the study among the other NFRs such as flexibility, robustness, versatility and changeability which depend on the system parameter, outcome parameter and perturbation type. As stated above, viability has no dependency on these

parameters and can be used as a unique criterion for assessing the ability of complex engineered systems under uncertainty. The second reason is the advantages of proposed model against qualification models such as Adams model [7] for quantification of viability.

The third reason is advantages of the proposed model against quantification models (Table 16.) which has been proposed for assessing other NFRs in the literature. The fourth reason is validation of the model based on a simple questioner that has been completed by 10 experts for each of case studies. Each question has been pointed from 0 to 100 by experts and the averages of 50 questioners are presented in Table 17.

As it has been represented in Table 17, the average assessment obtained from experts regardless of timeliness index is about 90% and illustrated that the model is accepted relatively. Also the low point in timeliness scale is related to complete search algorithm for clustering DSM matrix which is presented as the weak point of the model.

Table 17. Average points for distributed questioner

Row	Question	Average point
1	How much the model has the complete assessment of operational environment uncertainty in this case?	82%
2	How much the functional to physical mapping was rational in this case?	91%
3	How much the clustering outputs was rational in this case?	86%
4	How much the relationship of model elements was complete and rational?	95%
5	How much the model was timeliness?	43%
6	How much the viability obtained during the procedure in this case adapts with reality based on your technical judgment?	90%
8	How much the model can be useful for technical application and decision making based on this case?	93%
7	How much the model has expandability for using in other CES cases?	91%

5- CONCLUSION

Complex Engineered systems operate in dynamic environments and have long lifespan. So stakeholders need to design systems, which will continue to provide acceptable value for their intended life. There are numerous non-functional requirements (NFRs) that help systems to maintain their value delivery in spite of uncertainty. There is a lack of comprehensive model in the literature for assessing the ability of these systems under uncertainty conditions. To fill this gap, after reviewing non-functional requirements, viability was selected as a suitable criterion for assessing the ability of complex engineered system under uncertainty. A 7-step model was proposed for quantifying the viability value. In the proposed model, potential operational scenarios were identified and subsequently were scored for their likelihood and conditional impact. Then changes to functional requirements and system attributes necessitated by each operational scenario were determined and imposed on the impacted design variables. Furthermore, a sensitivity analysis was used to identify the design variables which are more reactive to the potential changes. These identified design variables were clustered for quantification of system viability using the information which was generated in different steps. Finally, the application of the proposed model was demonstrated by using a simplified illustrative example of a Synthetic Aperture Radar (SAR) satellite as a complex engineered system and all the inputs, the procedures and the outputs of the model were checked by experts to ascertain the logicity of the model. Developing novel clustering algorithms and applying the model in different case studies is proposed for future works.

REFERENCES

[1] R. Westrum, A Typology of Resilience Situations, in: Resilience Engineering: Concepts and Precepts, Ashgate, Aldershot, 2006, pp. 55-66.
 [2] Richards, M. G., Hastings, D. E., Ross, A. M. and Rhodes, D. H. (2009), 7.1.1 Survivability Design Principles for Enhanced Concept Generation and Evaluation. INCOSE International Symposium, 19: 1055-1070. doi:[10.1002/j.2334-5837.2009.tb01001.x](https://doi.org/10.1002/j.2334-5837.2009.tb01001.x)

[3] Smart, Ashley G., et al. "Cascading Failure and Robustness in Metabolic Networks." Proceedings of the National Academy of Sciences of the United States of America, vol. 105, no. 36, 2008, pp. 13223–13228.
 [4] Mekdeci, Brian, "Managing the impact of change through survivability and pliability to achieve viable systems of systems," Massachusetts Institute of Technology, 2013.
 [5] Fisher, David., Linger, Richard., Lipson, Howard., Longstaff, Thomas., Mead, Nancy., & Ellison, Robert. (1997). Survivable Network Systems: An Emerging Discipline (CMU/SEI-97-TR-013). Retrieved May 27, 2019, from the Software Engineering Institute, Carnegie Mellon University, <http://resources.sei.cmu.edu/library/asset-view.cfm?AssetID=12905>
 [6] A.M. Ross, D.B. Stein, D.E. Hastings, Multi-Attribute Tradespace Exploration for Survivability, Journal of Spacecraft and Rockets, 51(5) (2014) 1735-1752.
 [7] K.M.G. Adams, Non-functional Requirements in Systems Analysis and Design, Springer International Publishing, 2015.
 [8] A. Stevenson, Oxford dictionary of English. Oxford University Press, 2010.
 [9] Beesemyer, J.C., & Rhodes, D.H. (2012). A Prescriptive Semantic Basis for System Lifecycle Properties.
 [10] Nicola Ricci, Matthew E. Fitzgerald, Adam M. Ross, Donna H. Rhodes, Architecting Systems of Systems with Ilities: An Overview of the SAI Method, Procedia Computer Science, Volume 28, 2014, Pages 322-33.
 [11] Bartolomei, J. E., Neufville, R. , Hastings, D. E. and Rhodes, D. H. (2006), 9.1.3 Screening for Real Options "In" an Engineering System: A Step Towards Flexible System Development. INCOSE International Symposium, 16: 1241-1257. doi:[10.1002/j.2334-5837.2006.tb02809.x](https://doi.org/10.1002/j.2334-5837.2006.tb02809.x)
 [12] Pierce, Jeff. "Designing flexible engineering systems utilizing embedded architecture options." Vanderbilt University, Ph.D. Thesis, (2010).
 [13] C.A.J. Scott Ferson, Jon C. Helton, William L. Oberkampf, Kari Sentz, Summary from the epistemic uncertainty workshop: consensus amid diversity, Reliability Engineering & System Safety, 85(1-3) (2004) 355-369.
 [14] B. Mekdeci, A. M. Ross, D. H. Rhodes, and D. E. Hastings, "A taxonomy of perturbations: Determining the ways that systems lose value," IEEE International Systems Conference SysCon 2012, 2012, pp. 1–6.
 [15] A. Ross, H. McManus, D. Rhodes, D. Hastings, and A. Long, "Responsive Systems Comparison Method: Dynamic

- Insights into Designing a Satellite Radar System,” AIAA SPACE 2009 Conference & Exposition, 2009.
- [16] N. Ricci, A. M. Ross, and D. H. Rhodes, “A Generalized Options-based Approach to Mitigate Perturbations in a Maritime Security System-of-Systems,” *Procedia Computer Science*, vol. 16, pp. 718–727, 2013.
- [17] T. Mikaelian, D. H. Rhodes, D. J. Nightingale, and D. E. Hastings, “Model-based estimation of flexibility and optionability in an integrated real options framework,” in 2009 3rd Annual IEEE Systems Conference, 2009, pp. 224–229.
- [18] M. E. Fitzgerald, A. M. Ross, and D. H. Rhodes, “8.4.1 Assessing Uncertain Benefits: a Valuation Approach for Strategic Changeability (VASC),” *INCOSE International Symposium*, vol. 22, no. 1, pp. 1147–1164, Jul. 2012.
- [19] T. R. Browning, “Applying the design structure matrix to system decomposition and integration problems: a review and new directions,” *IEEE Transactions on Engineering Management*, vol. 48, no. 3, pp. 292–306, 2001.
- [20] R. E. (Ronnie E. 1970- Thebeau, “Knowledge management of system interfaces and interactions from product development processes,” 2001.
- [21] J. Jay Clark Beesemyer, *Empirically characterizing evolvability and changeability in engineering systems*, Massachusetts Institute of Technology, 2012.
- [22] B. Mekdeci, A. M. Ross, D. H. Rhodes and D. E. Hastings, “Pliability and Viable Systems: Maintaining Value Under Changing Conditions,” in *IEEE Systems Journal*, vol. 9, no. 4, pp. 1173-1184, Dec. 2015. doi: 10.1109/JSYST.2014.2314316
- [23] L. Chung, B.A. Nixon, E. Yu, J. Mylopoulos, *Non-Functional Requirements in Software Engineering*, 1 ed., Springer US, 2000.
- [24] M. Glinz, *On Non-Functional Requirements*, in: 15th IEEE International Requirements Engineering Conference (RE 2007), IEEE Delhi, India 2007, pp. 21-26.
- [25] J.J.G. Agis, S.S. Pettersen, C.F. Rehn, A. Ebrahimi, *Handling commercial, operational and technical uncertainty in early stage offshore ship design*, in: 11th System of Systems Engineering Conference (SoSE), IEEE, Kongsberg, Norway, 2016.

HOW TO CITE THIS ARTICLE

J. Gheidar-Kheljani, M.H. Karimi Gavarehski, M. Tahoori, Title, *A Method for Assessing the Ability of Complex Engineered Systems under Uncertainty* *J. Model. Simul.*, 52(1) (2020) 19-30.

DOI: [10.22060/miscj.2019.14645.5112](https://doi.org/10.22060/miscj.2019.14645.5112)

