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Detection of Detrimental Weak Emergent Behavior Considering Operational Factors: a Case Study in Search and Rescue

R.A. Haugen, S. Kokkula, *senior member, IEEE*, A. Ghaderi, G. Muller, and E. Syverud

***Abstract*— This paper applies the Design of Experiments approach for detecting detrimental weak emergent behavior of an Autonomous Surface Vessel operating in a dynamic environment on a Search and Rescue mission. The research utilizes Orthogonal Arrays in combination with regression analysis to systematically test the parameter space of an engineered system function. We explored the parameter space of interest and detected where the system model does not comply with a defined Measure of Effectiveness. The findings from this case study suggest that these methods enable a systematic exploration of the system's parameter space, allowing for effective detection of detrimental weak emergent behavior. This approach potentially enhances test coverage, expands system operating knowledge, and facilitates mitigation efforts more efficiently.**

***Index Terms*—Design of Experiments, emergent behavior, regression analysis, system testing**

I. INTRODUCTION

A. Background and Motivation

EMERGENT behavior can lead to costly delays in projects and hinder the overall success of system implementation. Additionally, operational use of systems often uncovers errors and undesired behavior, forcing system developers to do more systematic testing during the system development phase [1]. Engineering of systems for their operational environment requires alternative test approaches to go beyond mere isolated requirements testing and rather look at the superset of requirements.

Design of Experiments (DoE) is an approach to testing. In principle, DoE can extract maximum information through minimum testing, facilitating a cohesive, robust, and holistic test strategy to reduce emergence. DoE uses Orthogonal Arrays (OAs) that allow for a comparison between parameters and parameter values through regression analysis to enable efficient screening of the parameter space and subsequently also facilitate effective detection of detrimental weak emergent behavior.

As the state-of-art seems to claim clear benefits of DoE [2-5] but lacks research on an approach combining DoE and regression analysis in systems testing, we find this approach of interest to research in a case study to demonstrate its value in an industrial context.

B. Literature Review

The technique of defining and investigating selected test points / test cases within all possible combinations in an experiment involving multiple parameters is known as DoE [4, 5]. To make DoE easier and more attractive to industry, Dr. Taguchi developed the Taguchi method [3]. The Taguchi method uses OAs to minimize the number of test runs (or combinations) needed for an experiment [2]. DoE and the Taguchi method allows the designer to consciously identify the parameter combinations where the system parameters are statistically likely to have influence on the system performance [2].

Multiple Linear Regression (MLR) is the classical regression analysis technique that combines a set of input parameters in linear combinations, which correlate as closely as possible to the corresponding single output parameter [6].

We focus our efforts on weak emergence, including falsely perceived strong emergence. We define detrimental weak emergent behavior in this paper as parameter value combinations in a simulation that non-intuitively fails to meet the defined Measure of Effectiveness (MoE) for an engineered system.

"*Weak emergence*: The emergent property is reproducible and consistently predicted with simulation. *Strong emergence*: The emergent property is consistent with the known properties but, even in simulation, is inconsistently reproduced without any justification of its manifestation." [7] (p. 81-82).

"*MoE*: a measure that defines the acquirer's key indicators of achieving the mission needs for performance, suitability, and affordability across the life cycle." [8] (p. 97)

"*Engineered system*: a system designed or adapted to interact with an anticipated operational environment to achieve one or more intended purposes while complying with applicable constraints." [9] (p. 7)

Barboza et al. [10] describe how simulated virtual testing environments allow for low-cost ways to address possible

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R.A. Haugen, S. Kokkula, A. Ghaderi, G. Muller, and E. Syverud are with the University of South-Eastern Norway, (e-mail: rune.a.haugen@usn.no, satyanarayana.kokkula@usn.no, ali.ghaderi@usn.no, gerrit.muller@usn.no, elisabet.syverud@usn.no).

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hardware and software faults without using the real system, within the context of unmanned surface vehicles for monitoring and reconnaissance. We consider this to be a comparable context to our research.

Emergent behavior is the problem under investigation in this paper, and Rainey and Holland [11] provide various examples of emergent behavior:

- at war, weapon employment without human supervision has led to civilian aircraft being shot down,
- in wargaming, the human intellect not being rule-based has led to a shift in results,
- within the oil and gas industry, we have seen accidents like well explosions and oil spills because of unforeseen interactions, constraints, and variations.

Giammarco [12] provides a general methodology for exposing and controlling unexpected and unwanted behavior in complex systems. This methodology involves an emergent behavior analysis employing human reasoning together with automated tools providing new means for system designers to leverage positive emergent behavior and remove or minimize negative emergent behavior from their designs. The enabling technology behind this methodology called Monterey Phoenix is feasible for designers of complex systems in industrial applications ranging from customer experience to defense applications [12].

Monterey Phoenix is an enabling technology part of a new approach to ensuring good test coverage [12]. An older approach is DoE, which has a rich tradition and is still in use today with claimed benefits [13, 14].

Page et al. [15] introduce a framework for effective and efficient simulations. This framework consists of three capabilities: 1) grid or cloud-based execution, 2) DoE, and 3) robust data processing and visualization.

Freiesleben et al. [16] discuss the benefits created from combining DoE and Machine Learning (ML), claiming that the combination of these two can increase both the effectiveness and efficiency of a test process.

The Taguchi method [3], being a DoE method, has been researched for decades. We see examples of research on the Taguchi method to optimize the design for performance, quality, and cost [17-19], as well as additions to ensure a robust design in the light of aspects like dynamic failure mechanisms [20].

Freeman and Warner [21] claim system performance degradations not otherwise identified until operational use can be discovered using the tools that DoE provides, ensuring a defensible test coverage. Further, regression analysis allow for maximizing information gained from test data [21].

Director Operational Test & Evaluation [22], being an adviser to the Secretary of Defense in all Department of Defense matters related to Operational Test & Evaluation, advocates a DoE approach to testing of complex systems. The selected DoE approach uses screening experiments to ensure consideration of important parameters before sequential experiments extracting relevant information through refinement of parameters and levels, based on prior testing, for each quantitative mission-focused measure [21].

Programs that use DoE, such as the F-35 Joint Strike Fighter, have seen benefits in the order of millions of dollars in cost savings [13]. Cost savings from the use of DoE also applies to complex systems such as the Joint Direct Attack Munition and Joint Air-to-Surface Standoff Missile [14].

The state-of-art within the field of systems engineering is lacking research regarding the traditional approach of DoE in system testing over the last 20 years. Specifically, case studies from the industry to show that a DoE approach is still valuable for the industry in the age of Model-Based Systems Engineering and Artificial Intelligence.

C. Framing

This paper addresses the challenges associated with detecting detrimental weak emergent behavior during system testing for an Autonomous Surface Vessel (ASV) on a Search and Rescue (SAR) mission in a dynamic environment. Fig. 1. shows a photo of an ASV.

We focus on an ASV in its operational environment on a SAR mission. The operational environment involves the ASV interacting with both the dynamic environment and the vessel-in-distress (VID), see Fig. 4. The ASV and VID both have managerial and operational independence. The goal for the ASV's SAR mission is to detect the VID based on a distress call containing VID kinematic parameters (position, plus potentially heading and/or speed). The environment- and VID parameters together form what we call operational factors (noise parameters) being external input to the ASV's operating performance. The ASV is an engineered system.

We conduct this research within the field of systems engineering, to enhance that field's body-of-knowledge. This research should be relevant to various industries developing systems that are influenced by external factors during system in operations.

D. Research Objective and Questions

The objective of this research is to improve the test coverage for the case company to facilitate detection of detrimental weak emergent behavior in their systems. We seek to achieve this objective through utilization of a DoE approach based on findings from the literature review. The research will contribute to the body-of-knowledge with findings from a case study using DoE in the Norwegian high-tech industry company KONGSBERG. We defined the following research questions for this case study, scoped to a system performing level in an operational context:

Fig. 1. Example of an ASV from KONGSBERG

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- **Research question (RQ):** How can we increase the test coverage and detection of detrimental weak emergent behavior in engineered systems?
- **Sub-research question 1 (SRQ1):** How can we use a DoE approach to efficiently cover the parameter space of an engineered system?
- **Sub-research question 2 (SRQ2):** How can we use a DoE approach to effectively identify parameter value combinations that result in detrimental weak emergent behavior for an engineered system?

E. Paper Structure

The remainder of this paper is structured as follows: The Methods section provides a description of the methodology (combination of existing methods) in the approach we use in this paper. The Results section provides the results we obtained through the case study utilizing the selected methodology. The Discussion section provides answers to the research questions. Finally, the Conclusion section summarizes the paper, provides gained knowledge, defines limitations of the study, and proposes future research.

II. METHODS

The operating envelope of a system is met through design parameters that are selected for a required range, e.g., a boat can be designed to operate within a certain range of sea wave height. The required wave height range differs across boat designs. Operating temperature is an example of a parameter that can change within the same product line, e.g., a tropical climate vs a polar climate. In this example, it is up to the system architect to decide if the system should meet the full temperature range for all conditions or if the system should accommodate a limited temperature range. Any design parameter can therefore have a physical parameter space exceeding the actual operating range. Fig. 2 shows an example of the system parameter space for a system's operating envelope and a system's MoE envelope for a simplified six-dimensional parameter system.

The parameter ranges (axes) represent the different parameters and the value ranges we have tested. The envelopes represent outer contours for the parameter space having a certain commonality. Operations within the MoE envelope indicate success while operations outside the MoE envelope indicate failure. System operations breaching the MoE envelope for a subset of the parameter ranges are undefined until tested or checked against a set of MoE envelopes. A set of MoE envelopes focusing on different parameter ranges can together cover the entire operating envelope. A test case is a selection of parameter values we can connect through lines and compare to the envelopes. The Subject Matter Experts (SMEs) help identify interconnected parameters that form relevant supersets for a given scenario. In the example on Fig. 2, six parameters form a hexagon. The hexagon is in reality multidimensional, and the interconnections between the parameters are random as you can reorganize the hexagon parameters without violating any principles or rules.

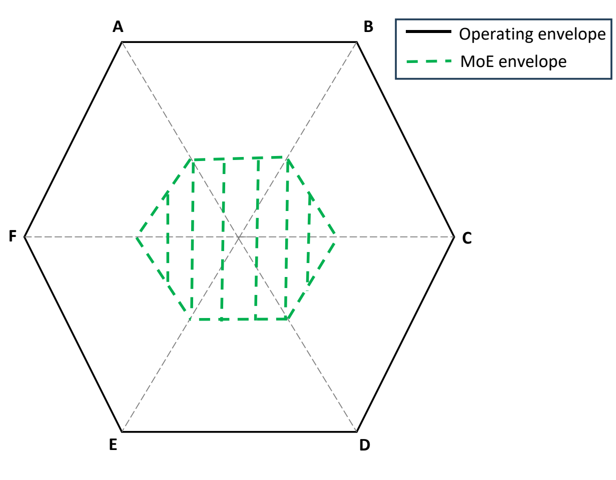

Fig. 2. Terminology

A. Current company approach to testing

In the traditional approach of system testing, system developers conduct system testing to confirm that the system meets the MoEs in specific parts of the operating envelope. The SMEs, who are experts in different functional areas (e.g., mission planning, propulsion, navigation, and sensors), identify critical operating points that are interesting for further investigation. These critical operating points are tested according to a test scheme considering parameter value combinations within a defined margin. The test approach is vulnerable to unknown weak emergence when the ASV is operating at parameter value combinations that are outside of the identified critical operating point's margin areas. On the other hand, resource constraints limit the number of possible test combinations to be executed. The untested areas inside the system operating envelope have an inherent risk of hiding detrimental system behavior. It is not possible to physically test all combinations of the multi-dimensional parameter space of an engineered system. To mitigate this, system developers design a test environment using simulation engines (sometimes in combination with hardware-in-the-loop) to represent the physical system. We research methods to explore a system's parameter space within a system's operating envelope to reduce the vulnerability of the current company test approach.

B. Step-by-step guide for a DoE approach

This step-by-step guide utilizes existing methods in an iterative way to efficiently test a system function in a large parameter space to effectively detect detrimental weak emergent behavior.

1. Definition of system MoEs serving as acceptance criteria for different system test cases.
2. Identification of parameters that might affect the defined MoE of a selected system test case.
3. Coarse scan of the parameter space for detecting the presence of detrimental system behavior.
   a. Selection of the parameters that indeed affect the defined MoE based on a screening of the parameter space with typically many parameters and few parameter levels.
   b. Mapping of parameter value combinations that meet the defined MoE to form MoE envelopes in the operating envelope based on a screening

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of the parameter space with typically few parameters and many parameter levels.

c. Selection of critical operating points where SMEs are uncertain whether the system meets the defined MoE.

4. Incremental fine scans of the parameter space around problematic areas for determining more accurately the detrimental system behavior boundaries.
   a. Selection of critical operating points that indeed exhibit detrimental system behavior.
   b. Determining the probability of detrimental system behavior within a defined area of a critical operation point, identifying parameter value combinations exhibiting this behavior, and mapping them in the parameter space.

The selected methodology entail leveraging the principle of parameter space exploration to screen and investigate the parameter space to detect detrimental weak emergent behavior. The authors selected these methods based on a thorough literature review related to detection of emergent behavior in engineered systems of various complexities [23], and a promising case study [24]. Resource constraints further enforces the use of Taguchi OAs compared to Full Factorial testing. Fig. 3 illustrates the principle of parameter space exploration via test points, in search of detrimental weak emergent behavior.

Following this step-by-step guide enhances our ASV performance knowledge. We can use this knowledge to propose mitigation strategies aimed at reducing or eliminating the detrimental weak emergent behavior. A side effect is that we could exploit potential beneficial weak emergent behavior when detected.

III. Case Study

The selected test case examines an ASV's VID detection capability during a SAR mission. The test case involves the engineered ASV system operating in a dynamic environment together with another system (VID). We do not aim for an optimal design related to the ASV, but for establishing the potential gap between its operating envelope and the part of the operating envelope where the ASV meets the defined MoE (referred to as MoE envelope).

The defined MoE entails successful detection of the VID. We classified the parameters of interest into two categories: continuous parameters, which can take any value within an interval, and discrete parameters, which take one value out of a given set of selectable values. As a simplification, this case study is limited to twelve parameters of interest including both continuous and discrete parameters. Table I presents an overview of the selected parameters, and the value ranges the ASV is designed to operate within. Default values are indicated in bold, these being the values that will give the highest probability of mission success confirmed by the SMEs. The low (level 1) and high (level 2) values could in principle be any two values. We aim to explore the main effects (such as the effect of wind speed) to identify areas in the parameter space prone to detrimental weak emergent behavior, and later detect parameter value combinations exhibiting such behavior. Interaction effects may be the reason for detrimental weak emergent behavior but are not of particular interest at this stage as we don't aim to find the root causes. Two-factor interaction effects (such as the combination of visibility and VID position) can have an effect, but higher-order interaction effects are likely not significant [4]. Our aim to find the main effects and the above statement regarding higher-order interaction effects reflects our selection of OAs.

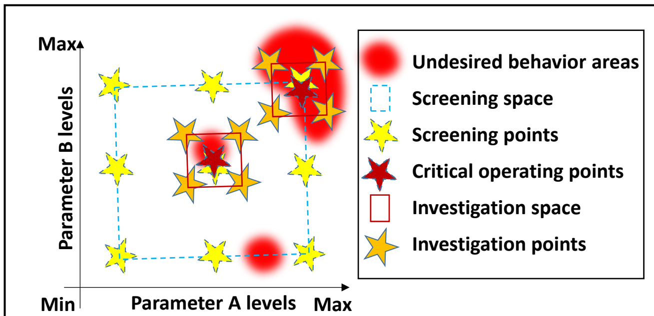

Fig. 3. Principle of parameter space exploration

TABLE I
PARAMETERS AND VALUE RANGES OF INTEREST

Type	Id	Name	Level 1 (Low)	Level 2 (High)	Unit
Noise / Cont.	**A**	Wind Speed	**0**	20	m/s
	B	Wave Height	**0**	10	m
	C	VID Position	**0**	4	km
	D	VID Heading	**0**	90	deg
	E	VID Speed	**0**	10	m/s
	F	Visibility	1	**18**	km
Control / Discr.	**G**	ASV Search Range	3	**5**	km
	H	ASV Camera Angle	Low (90*5)	**High (30*2)**	Deg. (Hor.*Ver.]
	J	ASV Camera Resolution	**Low (150)**	High (600)	dpi
	K	VID Size	Small (20*5*10)	**Large (80*15*25)**	Vol. (Length*Width*Height)
	L	ASV GPS	Off	**On**	NA
	M	ASV Observation Maneuver	Off	**On**	NA

Fig. 4 visualizes the parameters from a horizontal and vertical perspective. The position of the VID is simulated as perpendicular to the ASV heading. The wind and wave direction are set to the opposite of the ASV heading.

We performed the simulations using the company's simulator, Fig. 5. The simulator mimics the main dynamic behavior of the ASV, depending on the ASV's operational status, the ASV's configuration, and the environmental conditions. The simulation models vary in levels of idealization depending on the physical characteristics of the sub-system and the required accuracy of the representation. Depending on the nature of the sub-system, the sub-system models can be linearized simplifications of system behavior, discrete (on-off) representations, or more advanced physics-based behavior models. The environmental models represent the environmental parameters externally imposed onto the ASV. An example is the atmospheric model that calculates air parameters given the

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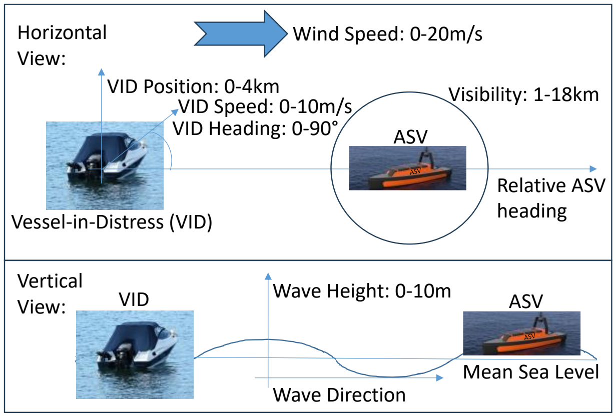

Fig. 4. Parameters of interest

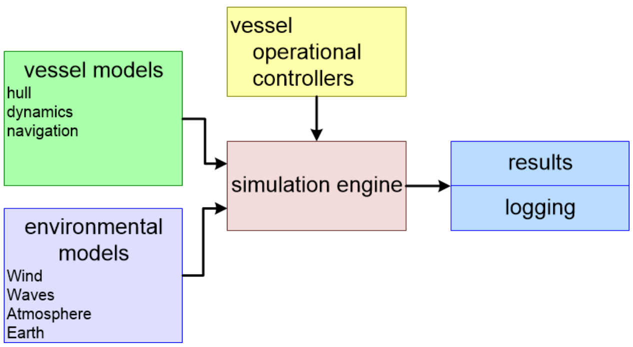

Fig. 5. Company simulator

temperature and atmospheric pressure at the ASV location. The vessel models represent the physical behavior of the ASV sub-systems, e.g., the propulsion system model simulates the propulsion output for a certain fuel input to the marine propulsion system. The simulation engine uses the propulsion output to calculate the position of the ASV when exposed to wind and waves. The vessel models are tested both at the sub-system level and also when integrated at the system level. The simulation engine is calibrated using operational (real-world) tests and is therefore seen as a good representation of the ASV dynamic behavior in the full operating envelope. A simulation engine like the one used in our case is developed by the company over many years, sometimes decades.

IV. Results

All results, including details on the transitions from screening to investigation, are available in the dataset [25]. Hereinafter, only a representative subset of the results is presented.

A. Screening for detection

First screening iteration:

We performed MLR to extract the parameter effects from twelve parameters SMEs assumed to be independent, see Table I. This MLR was based on a two-level Fractional Factorial DoE with 16 runs. Fig. 6 shows that six of the parameters revealed an effect while the other six parameters did not reveal any effect. The y-axis represents the average success rate as a function of the two values of each parameter on the x-axis. E.g.,

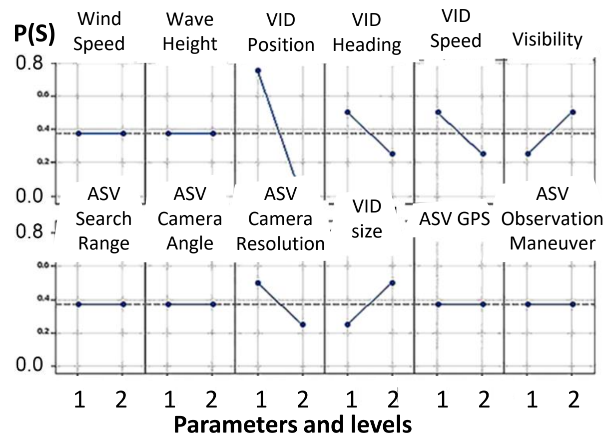

Fig. 6. First screening iteration's parameter effects

75% of the tests gave a positive response when parameter C (VID position) was at level 1 (0 km), while 0% of the tests did so when parameter C was at level 2 (5km). We used 5km as the level 2 value for parameter C in this first screening to verify the selected methodology, which we did in seeing a large negative effect at the high value of parameter C when the ASV is operating at a known problem area in the parameter space.

The main effects from the MLR can explain 93% of the variations in the response variable, indicating trustworthy parameter coefficients of our regression model we can use to evaluate parameter importance.

Following an evaluation session with SMEs, we proceeded with noise parameters (i.e., operational factors), see Table II, and tested the ASV's sensitivity under different settings of the two control parameters (J and K). We decided in the next step to continue with parameter J (camera resolution) and keep parameter K at high value (large vessel size) only.

Second screening iteration:

TABLE II
Second Screening Iteration's Data

			Level				
Type	**Id**	**Name**	**1**	**2**	**3**	**4**	**5**
Noise / Cont.	**A**	Wind Speed	0	5	10	15	20
	B	Wave Height	0	2.5	5	7.5	10
	C	VID Position	0	1	2	3	4
	D	VID Heading	0	22.5	45	67.5	90
	E	VID Speed	0	2.5	5	7.5	10
	F	Visibility	1	5.25	9.5	13.75	18
Control / Discr.	**J**	ASV Camera Resolution	Low (150)	High (600)			
	K	VID Size	Large (80*15*25)				

The goal of the second screening iteration was to see what part of the parameter's value range affected the ASV's detection success. In a new brainstorming session, the SMEs wanted to include some intermediate noise (environmental and VID) parameter values expecting different parts of the value

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range would yield different effects. We added three intermediate values for parameters A to F and used a L25 OA, while keeping parameter J at two levels. See Table II for the parameter values.

The results of MLR revealed that the camera with low resolution is performing well throughout the parameter space, but the camera with high resolution has much less coverage of the parameter space where the defined MoE is achieved. See Fig. 7 for the effects of the six parameters for the camera with low resolution and Fig. 8 for the camera with high resolution. The main effects from the MLR are able to explain 77% and 72% of the variations in our data for the low- and high camera resolutions respectively indicating trustworthy parameter coefficients of our regression model we can use to evaluate parameter value importance.

One out of twenty-five tests did not meet the defined MoE, i.e., not detecting the VID, for the camera with low resolution. This is the only information we could obtain for further investigation. Seven out of twenty-five tests did not meet the defined MoE for the camera with high resolution, leaving us with a good rationale for further investigation. We saw a positive surprise (beneficial weak emergent behavior) when we increased the value of parameter D (VID heading) from level 2 (22.5 deg) to level 4 (67.5 deg). The ASV obtained a better aspect angle of the VID going from the second to the fourth value of parameter D, when parameter C was at other values than 0 km (start value, in Table II). At this point we did some more testing going in opposite direction for parameter C (i.e., ASV with worse aspect angle) and noted a negative surprise (detrimental weak emergent behavior). After reasoning about these surprises, we increased our knowledge sufficiently to reduce our subjectively experienced emergence level from weak (non-intuitive) to simple (intuitive). The SMEs selected a parameter value combination (marked in red in Fig. 8) to proceed with in the following investigation phase for the high-resolution camera. The selection process is described in detail in the dataset [25], and the outcome is a prioritized list of parameter value combinations. The SMEs are uncertain of the result (detection vs. no detection) of the listed parameter value combinations and interested in exploring these further.

Fig. 9 presents an example MoE envelope for high-resolution camera results, based on screening presented in Fig. 8. One can notice that this MoE envelope does not cover a VID position more than 2 km away from reported position in the distress call. Fig. 10 shows another MoE envelope example for the high-resolution camera where the operating envelope of 4km VID position is met. The MoE envelope related to the low-resolution camera results, based on screening presented in Fig. 7, covers the entire operating envelope. On both Fig. 9 and 10, the green (dashed) contour indicates a parameter value combination where the ASV performance is meeting the defined MoE. We can further assume that all parameter value combinations within the MoE envelope are OK. We conducted some additional confirmation runs to verify this assumption. The black (bold) lines indicate where the ASV is expected to meet the MoE and we have tested (trial and error) to do so by testing one parameter

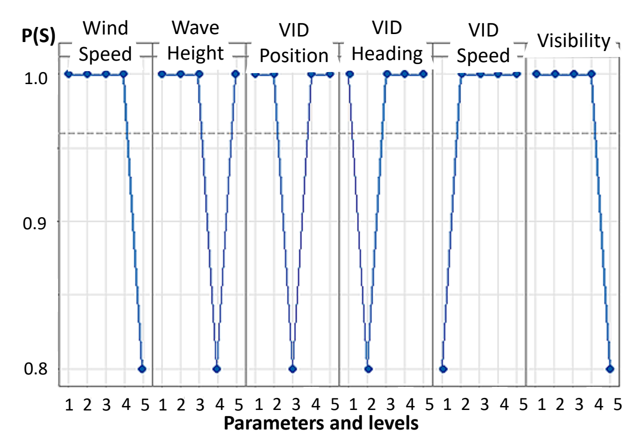

Fig. 7. Second screening iteration's parameter effects, low-resolution camera

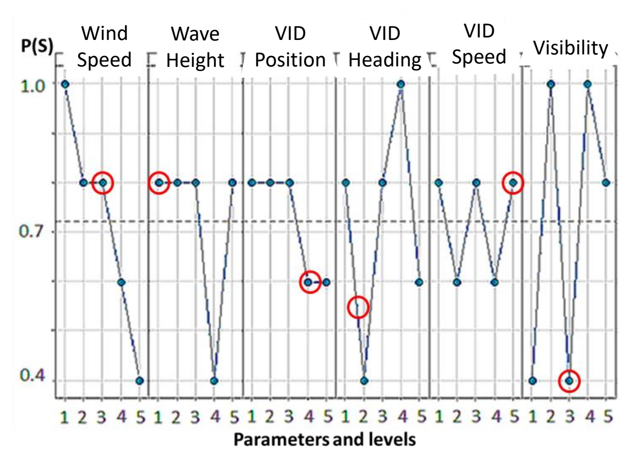

Fig. 8. Second screening iteration's parameter effects, high-resolution camera

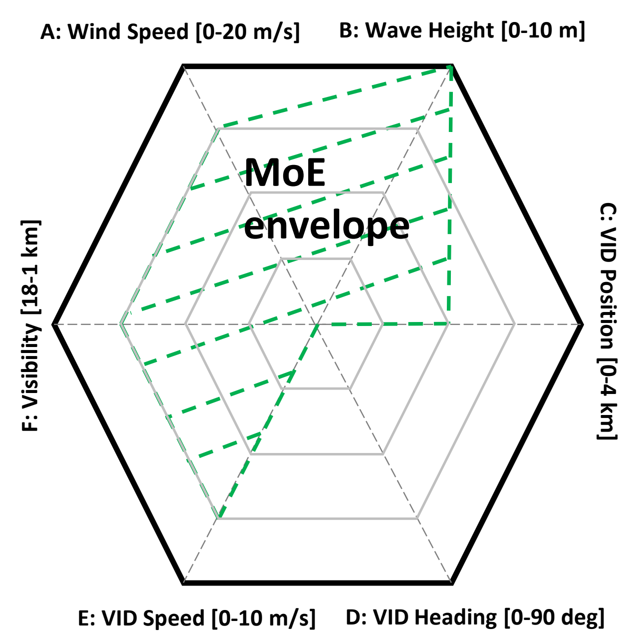

Fig. 9. MoE envelope for high-resolution camera not meeting parameter C operating envelope

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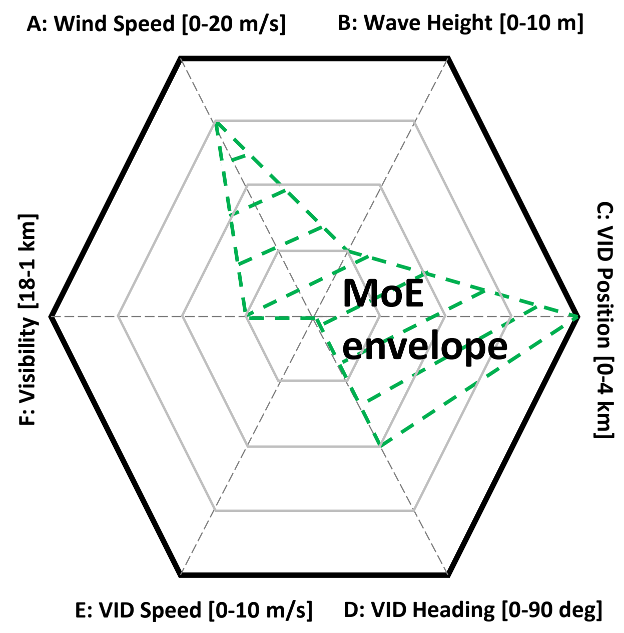

Fig. 10. MoE envelope for high-resolution camera meeting parameter C operating envelope

at a time at its maximum level while holding the other parameters at their minimum values. The area between the black (bold) line and the green (dashed) contours represents the parameter space where the ASV performance is conditional to the parameter value combinations. Outside the black (bold) contour, the ASV performance does not meet the defined MoE for the parameter space we investigated. We found that the ASV is sensitive to the noise parameters when using camera with high resolution, and users should be careful when selecting this type of camera resolution in SAR operations. Considering the obtained situational awareness of the ASV (lack of) performance to meet the defined MoE throughout the parameter space, we can now provide feedback to the system designers to facilitate potential mitigation efforts. Also, we can start further investigation efforts to increase our knowledge in potential areas of interest revealed during the screening phase.

B. Investigating for desired knowledge

First investigation iteration:

This first investigation iteration explored parameter space in relation to the negative responses from tests in the screening phase. We combined SMEs' knowledge as well as knowledge obtained through the screening experiments (from previous section) to select relevant parameters value combinations. We selected the parameter value combinations (center values, in Table III) that SMEs perceived had the highest probability of exposing undesired system behavior with the low camera resolution. See Table III for an overview of the selected parameter values for the first iteration of the investigation phase of our case study. We provide here an example regarding wind speed, where the selection process was:

- We saw a drop in system performance between 15 and 20 m/s wind speed, ref. Fig. 7
- We divided the value range [0-20] by 10 to set possible center values to choose from and excluded the extremes (0 and 20 m/s)
- As we had already tested 20 m/s, we set 18 m/s as max value
- We decided on one step length to be 10% of the value range (20 m/s) being the range between the center value and min/max values
- The center value then became 16 m/s and the min value 14 m/s

TABLE III
FIRST INVESTIGATION ITERATION'S DATA

Type	Id	Name	Center Value	Level 1 (Low)	Level 2 (High)	Unit
Noise / Cont.	A	Wind Speed	16	14	18	m/s
	B	Wave Height	7.5	6	9	m
	C	VID Position	2.775	1.8	3.75	km
	D	VID Heading	81	72	90	deg
	E	VID Speed	7	6	8	m/s
	F	Visibility	16.3	14.6	18	km
Control / Discr.	J	ASV Camera Resolution	Low (150)	Low (150)	Low (150)	dpi

The simulation results left us with one unexpected undesired response (QA=0). See Table IV for the results. QA stands for quality attribute [2] of a simulation, where the response can be either 0 (failure) or 1 (success). Tests numbered Tx, x∈[1..n]. T1-8 are the 8 tests of this L8 OA.

TABLE IV
FIRST INVESTIGATION ITERATION'S RESULTS

Tests	Parameters							QA
	A	B	C	D	E	F	J	
T1	14	6	1.8	72	6	14.6	Low	1
T2	14	6	1.8	90	8	18	Low	0
T3	14	9	3.75	72	6	18	Low	1
T4	14	9	3.75	90	8	14.6	Low	1
T5	18	6	3.75	72	8	14.6	Low	1
T6	18	6	3.75	90	6	18	Low	1
T7	18	9	1.8	72	8	18	Low	1
T8	18	9	1.8	90	6	14.6	Low	1

We decided to continue investigating the discovered negative response (QA=0), to determine its size, and contour in the parameter space.

Further analysis of the first investigation for QA=0:

For test number 2 in Table IV, one can see the ASV missed to detect the VID (i.e., QA=0). We took a closer look at this parameter value combination by selecting this as center values for the next iteration. Then, we used a Taguchi L8 OA with low and high values +/-10% of the parameter value range offset from the center values. We continued cutting the offset in half (5%, 2.5%, etc.) until we found the transition into the parameter space exhibiting detrimental weak emergent behavior (between 0.16% and 0.08% offset).

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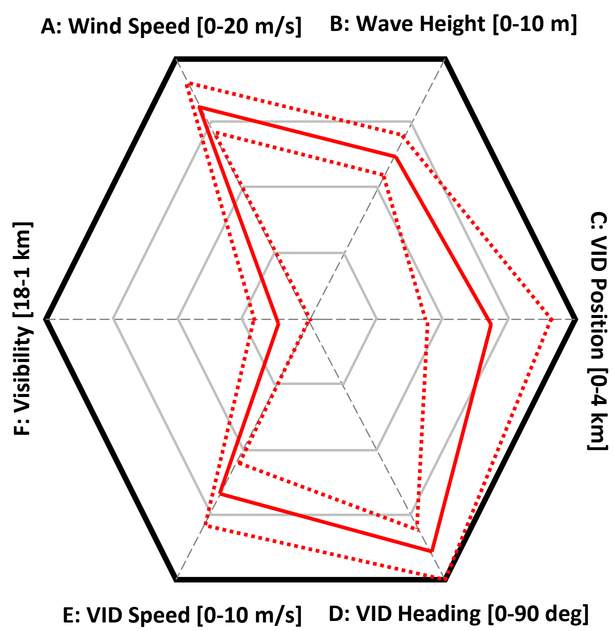

Fig. 11. Detrimental weak emergent behavior example for low-resolution camera

Through the investigation phase, we have been able to find a small region within the MoE envelope that exhibits detrimental behavior. See Fig. 11 for the identified parameter value combination exhibiting detrimental behavior (red solid line) and the investigated area of the parameter space (area between the dotted red lines). We found detrimental behavior for all runs using 0.08% offset and no runs using 0.16% offset, indicating a probability between 0.8 and 1.6% of detrimental behavior within the investigation area of the parameter space (area between the dotted red lines). All responses gave a positive result until we were very close to the center values, indicating a small region in the parameter space exhibiting detrimental weak emergent behavior. Based on our experimentation with the low camera resolution, the ASV should not be sensitive to the noise parameters and be robust for operations within the entire operating envelope.

TABLE V

SECOND INVESTIGATION ITERATION'S DATA

Type	Id	Name	Center Value	Level 1 (Low)	Level 2 (High)	Unit
Noise / Cont.	A	Wind Speed	10	8	12	m/s
	B	Wave Height	1.5	0	3	m
	C	VID Position	3.15	2.75	3.55	km
	D	VID Heading	14	7	21	deg
	E	VID Speed	9	8	10	m/s
	F	Visibility	9.5	7.8	11.2	km
Control / Discr.	J	ASV Camera Resolution	High (600)	High (600)	High (600)	dpi

Second investigation iteration:

The second investigation iteration explored the detrimental weak emergent behavior concerning the second selected parameter center value combination. Based on SME knowledge and data from the screening experiments, we selected a center value combination using high camera resolution. See Table V for an overview of the selected parameter values for the second investigation iteration of our case study.

The simulation results left us with six unexpected undesired responses (QA=0). See Table VI for the results.

TABLE VI

SECOND INVESTIGATION ITERATION'S RESULTS

Tests	Parameters							QA
	A	B	C	D	E	F	J	
T9	8	0	2.75	7	8	7.8	High	1
T10	8	0	2.75	21	10	11.2	High	1
T11	8	3	3.55	7	8	11.2	High	0
T12	8	3	3.55	21	10	7.8	High	0
T13	12	0	3.55	7	10	7.8	High	0
T14	12	0	3.55	21	8	11.2	High	0
T15	12	3	2.75	7	10	11.2	High	0
T16	12	3	2.75	21	8	7.8	High	0

We decided to continue investigating the discovered negative responses, to determine their size and contour in the parameter space.

Further analysis of the second investigation for QA=0:

We selected the parameter value combinations providing the negative responses as center values for six investigations, i.e., test numbers 3-8 in Table VI. For these six center value combinations, we performed tests based on a Taguchi L8 OA with low and high values +/-10% of the parameter ranges offset from the center values.

Three of the investigations provided the following results:

i. For experiment 4 in Table VI, 8 out of 8 tests provided a negative response (QA=0)
ii. For experiment 5 in Table VI, 7 out of 8 tests provided a negative response (QA=0)
iii. For experiment 6 in Table VI, 4 out of 8 tests provided a negative response (QA=0)

We continued doubling the offset (20%) until we could confirm that we had exceeded the system operating envelope, indicating a transition zone in the range of 2 to 4 km VID position in the parameter space exhibiting detrimental weak emergent behavior.

Through the investigation phase, we have been able to provide a set of parameter value combinations exhibiting detrimental behavior, including their probabilities. We determine the probabilities based on a set of experiments around the parameter value combination we have detected to exhibit detrimental behavior as described above. See Fig. 12 for an example of a detected parameter value combination exhibiting detrimental behavior (red solid line) and the investigated area of the parameter space (area between the dotted red lines). This example of detrimental behavior provided us with 100% probability of mission failure (no detection) as 8 out of 8 experiments provided a negative response (no detection). Based on our experimentation with the high camera resolution, the ASV is sensitive to the noise parameters and not robust for operations within the entire operating envelope.

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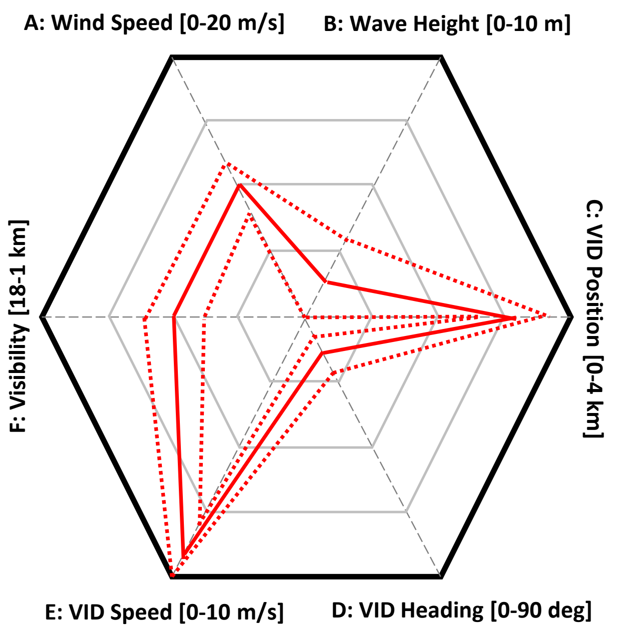

Fig. 12. Detrimental weak emergent behavior example for high-resolution camera

V. Discussion

We find that the selected methodology can identify the gap between the system operating envelope and system MoE envelopes, being the part of the parameter space prone to detrimental weak emergent behavior. Based on this identified gap, we know where to look for specific parameter value combinations resulting in detrimental weak emergent behavior. Table VII samples tests from Table IV and Table VI resulting in detrimental behavior.

TABLE VII
Detrimental Weak Emergent Behavior Examples

Tests	Parameters							QA
	A	B	C	D	E	F	J	
T2	14	6	1.8	90	8	18	Low	0
T11	8	3	3.55	7	8	11.2	High	0
T12	8	3	3.55	21	10	7.8	High	0
T13	12	0	3.55	7	10	7.8	High	0
T14	12	0	3.55	21	8	11.2	High	0
T15	12	3	2.75	7	10	11.2	High	0
T16	12	3	2.75	21	8	7.8	High	0

Our selected methodology has a limitation in the distance between test points (step length between parameter values) within the parameter space for the screening phase, which results in an uncertainty equal to the step length. However, we can control the step length to decide the size of the uncertainty of the MoE envelope. Also, this step length can make the screening phase vulnerable to non-linearities. Reducing this vulnerability is a trade-off considering resources to run more tests in the screening phase. For the investigation phase, we saw a limitation through a comparison to a Full Factorial. A Full Factorial will reveal more parameter value combinations resulting in detrimental weak emergent behavior, expanding the list of parameter values resulting in detrimental weak emergent behavior in Table VII. The Full Factorial revealed 40 such parameter value combinations in 64 runs compared to 6 in 8 runs from the L8 OA in Table VI. Regression analysis results of the Full Factorial showed higher-order interaction effects, explaining the gap we see between the operating envelope and the MoE envelopes. However, the most important information to convey as feedback to system design is obtained through our selected methodology. The most important information is related to the gap between the system MoE envelopes identified (green area in Fig. 9 & 10) and the system operating envelope (black contour in Fig. 9 & 10), which we obtain through the data we collect and analyze. If this gap is big, revealing a large part of the parameter space being prone to detrimental weak emergent behavior, mitigation efforts should be initiated by the development project. Performing Full Factorials instead of our chosen OAs in this case study would have resulted in 52 315 tests compared to 259 tests, being about 2.3 orders of magnitude reduction in testing efforts. The latter is a significant contribution to cost and schedule savings for a project aiming for full test coverage. The detection rate of detrimental weak emergent behavior in our screening phase was 28%. Compared to a “sunny day” (default case and changing one parameter at a time) test approach that would not have detected any of the detrimental weak emergent behavior, our selected methodology have demonstrated to be effective in a case study. The typical challenge with lack of resources early in a project is reduced through our selected methodology, as they can find problems early and facilitate low-cost mitigations.

In the ASV case with a low-resolution camera, we don’t recommend any mitigations. The ASV is not sensitive to noise parameters using this camera type.

In the ASV case with a high-resolution camera, we recommend mitigation efforts to close the gap between the system operating envelope and the system MoE envelopes either through ASV design updates or changes to its operating procedures. The ASV can meet the MoE for a larger part of the operating envelopes if the requirements are flexible depending on a set of conditions, ref. Fig. 9 compared to Fig. 10. E.g., the requirement related to VID range can be 4 km under conditions within the MoE envelope in Fig. 10 but only 2 km under conditions within the MoE envelope in Fig. 9. Then, we manage to both keep the required performance for one particular parameter in one specific MoE envelope and make necessary adjustments to cover the entire operating envelope with a set of different MoE envelopes. We can create different MoE envelopes based on our simulation results that in combination can cover the entire operating envelope. However, we can only use one MoE envelope at a time when considering the ASV performance in a given situation. Another potential solution is to always operate the ASV with low camera resolution when the noise parameters are not within any MoE envelopes for the high-resolution camera.

We confirmed all results through repetitions. For a complete case study, the methodology must be repeated iteratively for all parameter value combinations that show a large enough reduction in the probability of success to make the SMEs uncertain about the result.

In the remainder of this section, we provide answers to the posed research questions.

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SRQ1: How can we use a DoE approach to efficiently cover the parameter space of an engineered system?

OAs are designed to systematically explore a given parameter space in a balanced manner, ensuring unbiased analysis of the test data. The choice of parameter value combinations for testing is guided by the principle of extracting maximum amount of information with the fewest possible tests for a given resolution, minimizing overlapping testing. The DoE framework offers a wide variety of OAs to choose from. Additionally, we can modify OAs within the Taguchi framework to suit our specific needs. Roy et al. [2] suggests that reducing the number of parameters in an OA is possible, and we did this in the investigation iterations by omitting the last column of all the L8 OAs. By using OAs wisely, we can cover the entire parameter space with amount of tests dependent on the selected resolution to obtain the desired information. When dealing with many parameters, a screening experiment can be a good starting point to identify the most important parameters- and values. In our case, we saw in our first screening step that we were able to down-select the amount of parameters from twelve to six. Further, we saw in our second screening step that we were able to see where in the value range of each parameter we should focus our continuing efforts. In both these screening steps we utilized DoE in tandem with regression analysis to extract parameter effects and establish MoE envelopes for a system function. As demonstrated in this case study, this methodology can efficiently explore the parameter space of an engineered system considering operational factors in an operational context.

SRQ2: How can we use a DoE approach to effectively identify parameter value combinations that result in detrimental weak emergent behavior for an engineered system?

Information from a screening phase is paramount to start a reasonable investigation effort. In our case, we conducted a perimeter investigation around an MoE envelope established in the screening phase for a small enough area to assume linearity in the results. Fig. 8 shows the ASV behavior throughout the operating envelope is not linear. We performed two investigations to evaluate the ASV's sensitivity to noise parameters under two different control parameter settings. First, we investigated the ASV using a low-resolution camera. We found that the ASV is not sensitive to noise parameters, except for one parameter value combination within the operating envelope. Second, we investigated the ASV using a high-resolution camera. We found that the ASV performance is sensitive to noise parameters, as the ASV performs below the defined MoE for a large part of the operating envelope. Even though the ASV can perform according to stated requirements in isolation, a more systematic testing of the operating envelope revealed an ASV performance that is not in line with the customer's expectations (i.e., defined MoE).

In our investigation, we employed DoE and regression analysis to explore areas around identified MoE envelopes (based on defined MoEs) of an engineered system considering operational factors in an operational context. As demonstrated by this case study, this methodology can be efficiently utilized to potentially and effectively detecting detrimental weak emergent behavior for an engineered system.

RQ : How can we increase the test coverage and detection of detrimental weak emergent behavior in engineered systems?

The two main steps discussed for the SRQs constitute the building blocks for exploring the parameter space for detecting detrimental weak emergent behavior during system testing of an engineered system in an operational context. If we apply these methods iteratively, utilizing prior knowledge and simulation results, we will be able to efficiently establish the MoE envelopes for a system function. First, DoE using OAs in tandem with regression analysis allows for a systematic screening of the system performance, ensuring comprehensive test coverage with minimal testing. Second, these methods allow for a systematic investigation around the established MoE envelopes to detect detrimental weak emergent behavior. Combining prior knowledge with DoE and regression analysis can guide us to the information we seek, as well as providing us with a good rationale for what to test. We were able to find a part of the parameter space where the ASV performance was not good enough, e.g., when we used the high-resolution camera in combination with the VID being sufficiently positioned away from the reported position (due to position, heading, and speed). An important take-away is that the ASV performance varies across the parameter space, and this variation is not intuitive. Therefore, our selected methodology can be helpful in mapping the performance of an engineered system throughout its operating envelope to find where it meets a defined MoE and where it is prone to detrimental behavior. Furthermore, we can find the probability and examples of such behavior within a defined region related to the MoE envelopes. Finally, we can map the size and contour of the detrimental behavior areas in the parameter space.

VI. Conclusion

Engineered systems typically have a challenge with undesired non-intuitive system behavior (detrimental weak emergent behavior), which eventually will manifest in operational use. Industry needs a better testing strategy to cope with this challenge. In this work, we selected methods to detect detrimental weak emergent behavior during system testing of an engineered system in an operational context with a dynamic environment. We used OAs for test setup and subsequent regression analysis to extract the parameter effects and the probability for detrimental weak emergent behavior throughout the parameter space, which can facilitate an efficient and effective test process. The selected methodology have enabled us to systematically explore the parameter space of an engineered system, revealing previously unidentified undesired non-intuitive system behavior. Specifically in this case study, the selected methodology have enhanced our knowledge of an engineered system by detection of unknown detrimental weak emergent behavior through iteratively combining existing methods in a structured and systematic manner until we achieved the desired level of understanding for a specific function in our system of interest.

The selected methodology allow for a potentially efficient screening of the system parameter space to establish an overview of the system capability to meet a defined MoE throughout its operating envelope. We have demonstrated the use of the selected methodology in a case study to identify the gaps in the operating envelope of an ASV. A Full Factorial DoE approach would require additional efforts of about 2.3 orders of magnitude in this case study. We found the detection per test ratio was 40/64 (62.5%) for a Full Factorial vs. 6/8 (75%) for a Taguchi L8 OA. The ability to quickly gain a coarse situational awareness leverages the capability to find problems early and facilitate less cost driving mitigations. We also consider the demand for resources to be low, suitable for an early project phase, which typically involves scarcity of resources.

This research uses existing methods (OAs and regression analysis) and iterate through different phases (screening and investigation), guided by SMEs. The selected methodology quickly helped us to establish a situational awareness of what part of the parameter space being prone to detrimental weak emergent behavior and not in our SAR case study. Our main contributions are: 1) potentially enabling methodology for early- and continuous validation, 2) potentially feasible methodology to efficiently explore the parameter space to effectively detect detrimental weak emergent behavior of an engineered system in an operational context with dynamic environment, 3) an industrial case study utilizing the selected methodology, where the results provided confidence in applying this approach.

The main benefit and added value of doing system testing in the described iterative and exploratory way compared to the traditional way of focusing on single- or a limited set of requirements is to facilitate for mitigation efforts leading to less sensitive systems or more tailored utilization. Usually, verification and validation tests check the system conformity with respect to single requirements or a set of requirements. However, requirements may not be efficiently traced to test cases. Differently, the described methodology systematically checks the system conformity with a defined set of requirements, which we could further exploit to maximize the efficiency in testing through minimizing the amount of tests in order to verify the requirements.

We envision that our selected methodology will in general be suitable for not safety-critical systems, when resources are limited.

The effectiveness of this methodology is mainly limited by the resolution of the first screening, where automation processes can support through enabling increased test coverage and resolution. While this case study is limited in scope as it only researches one case for one system from one company in Norway within the maritime industry, future work is necessary to obtain more data in different settings to validate how efficient and effective this methodology is across various types of systems and contexts and be able to substantiate any generalization. Applicability of our selected methodology in different domains should be tested to build body-of-knowledge. Further, we could expand our assessments of uncertainty in line with Oberkampf and Roy [26]. Additionally, exploring how automation processes including ML could increase test coverage and resolution would be beneficial.

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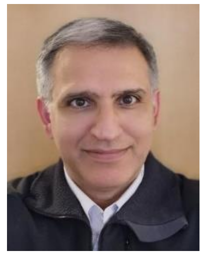
R.A. Haugen is an industrial-PhD candidate at the University of South-Eastern Norway (USN). He was in service with the Royal Norwegian Air Force (RNoAF) from 1997 to 2003, including graduation from the RNoAF Officer Candidate School in Stavern (1999) and the RNoAF Academy in Trondheim (2001). He holds both a BSc (2006) and a MSc (2013) in Systems Engineering from USN. He has worked as a design engineer at FMC Kongsberg Subsea from 2006 to 2008 (3D modeling), and as a system engineer at Kongsberg Defence and Aerospace since 2008 (system design and system test).

S. Kokkula received his PhD from the Norwegian University of Science and Technology (NTNU), Trondheim, Norway. From 2006 to 2016, he was employed as a Specialist Engineer in Structural Analysis at FMC Kongsberg Subsea AS. In August 2017, Dr. Kokkula joined the University of South-Eastern Norway (USN) as an Associate Professor of Systems Engineering. He serves as a Program Coordinator for Industry Master in Systems Engineering and Systems Engineering specialization coordinator for Master in Innovation and Technology Management at USN. Dr. Kokkula is a Certified Systems Engineering Professional (CSEP) by the International Council on Systems Engineering, and a Senior Member of the Institute of Electrical and Electronics Engineers.



A. Ghaderi earned his M.Sc. degree in Mathematics from the Norwegian University of Science and Technology (NTNU) in 1997 and went on to obtain his Ph.D. in Chemical Engineering from the University of Surrey, UK, in 2006. Between 1997 and 2006, he served as an Assistant and Senior Researcher at Tel-Tek. He then transitioned to the role of Senior Technologist at the Renewable Energy Corporation (REC) from 2007 to 2012, where he contributed to the development of high-efficiency solar cells. Since 2018, he has held the position of Associate Professor in Mathematics at the Department of Mathematics and Science Education at the University of South-Eastern Norway (USN). His research interests encompass Bayesian statistics, information theory, and also their applications in modelling human behaviour as well as engineering systems.

G. Muller, originally from the Netherlands, received his MSc in physics from the University of Amsterdam in 1979. He worked from 1980 until 1997 at Philips Medical Systems as a system architect, followed by two years at ASML as a manager of systems engineering, returning to Philips (Research) in 1999. Since 2003 he has worked as a senior research fellow at the Embedded Systems Institute in Eindhoven, focusing on developing system architecture methods and the education of new system architects, receiving his PhD in 2004. In January 2008, he became a full professor of systems engineering at the University of South-Eastern Norway. He continues to work as a senior research fellow at the Embedded Systems Institute in Eindhoven in a part-time position. All information (System Architecture articles, course material, curriculum vitae) can be found at: Gaudí systems architecting http://www.gaudisite.nl/

E. Syverud is an Associate Professor in systems engineering at the University of South-Eastern Norway. She received her MSc in Aerospace Engineering from the University of Kansas, US, and her PhD in Thermal Energy from the Norwegian University of Science and Technology in Trondheim, Norway. She started her industrial career in 1993 and has worked in multiple roles in the oil & gas and defense industries for 20 years. She joined the USN in 2019.