An improved approach for on-board distribution system robustness estimation in early-stage ship design

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AN IMPROVED APPROACH FOR ON-BOARD DISTRIBUTION SYSTEM ROBUSTNESS ESTIMATION IN EARLY-STAGE SHIP DESIGN

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Abstract. Reliability and survivability play a key role in the ship operation and ship design process of navy ships, but increasingly also of complex commercial vessels. These requirements prove relevant for different elements within the ship design scope, including the distribution system design of data, energy and fluid (water, fuel, oil, etc.). In early-stage ship design, distribution system robustness estimation is crucial in performing a substantiated trade-off between system availability and system investment costs. Van Mieghem et al. have developed a framework for computing topological network robustness; a generally applicable robustness approach using a graph representation as network system model. This framework has been applied on on-land power grids and more abstract networks such as the internet. However, due to the general nature of the framework, the applicability of the framework to on-board distribution systems is not self-evident. In this study, the required assumptions and adjustments to apply this mathematical approach to on-board distribution systems are described. Moreover, the usefulness of this method for system robustness estimation in early-stage ship design is considered and demonstrated. In conclusion, an improved robustness estimation of distribution systems makes for an overall more reliable ship; a property to be pursued for increasingly complex ships.

Keywords: On-board energy distribution systems, System robustness and vulnerability, Early-stage ship design and system design, Network Theory.

1. Introduction

Certain ship types can be regarded as complex systems [2]. One could in fact argue that all ships are complex systems, given their large number of components and the many multidisciplinary interactions between those components and sub-systems. According to Rhodes and Ross [3], there are five distinct aspects when engineering complex systems: structural, behavioural, contextual, temporal and perceptual aspects. The first two aspects are common practice in engineering complex systems and are applied using model-based systems engineering approaches. The structural aspects are related to system components and their interrelationships; which is the focus of this study. Ship subsystems, such as on-board distribution systems, first need to be improved to improve the overall structural aspects. In this case, *improving* means making the ship, more specifically its systems and components, more robust. The reasons for isolating the robustness element from the total ship improvement is explained below.

First, significant steps are expected in the development of autonomous surface vessels (ASV) during the next five to ten years [4]. Remote-controlled vessels with reduced crews are considered the first step on the track to fully autonomous vessels. It is generally assumed that autonomous vessels improve safety, increase efficiency and provide greener ship traffic [5]. However, Haugen et al. [5] state that, despite the decrease in accidents caused by human error, new forms of error might occur. Some of those errors are currently averted by the crew; a practice that becomes increasingly complex with a higher grade of autonomy, i.e. fewer crew members. To minimise these risks, an improvement in the robustness of on-board systems is required to ensure crew- and public safety. This is one reason to intensify our focus on robustness (with all its different aspects) of on-board systems.

Second, the selection of system components, especially in the power and propulsion system (PPS), provides a possibility to enhance the sustainability. Han [6] states that pollution emissions from international

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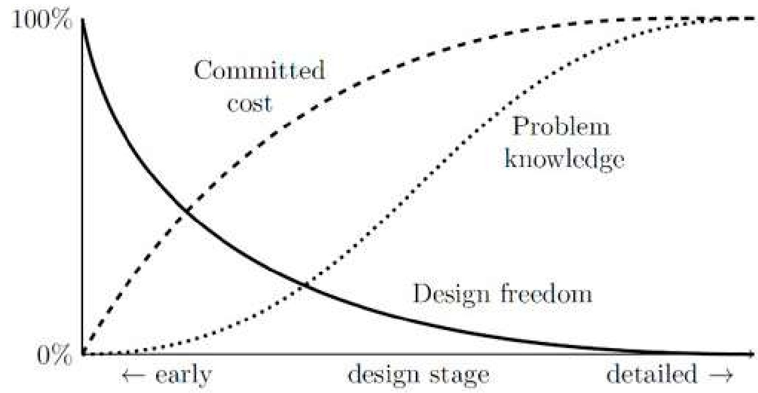

Figure 1. Design Timeline [9]

ocean-going vessels significantly impact air quality and public health. Technology strategies such as replacing or upgrading older engines or improving fuel qualities and/or type can be implemented in current and future marine vessels to improve environmental performance [7]. According to Nguyen et al. [8], objective measures are to be applied to compare conventional and advanced propulsion systems, including a robustness measure, which is the second reason to intensify our focus on robustness of on-board systems.

The third and last argument for improving system robustness can be found for ships with characteristic operational profiles, such as naval vessels, sailing yachts and cruise ships. These ships often involve multiple interconnected (electrical/mechanical) power, oil (fuel) and (chilled) water distribution systems, making a failure of a single system of significant influence on the whole ship performance and functionality. Recently, extensive research on improving the robustness of naval vessels has been conducted. These research efforts aimed to improve a vessel's survivability during a hostile attack, see e.g. [9, 10, 11], especially since some weapon systems require multiple distribution systems to function [10]. Therefore, these supporting distribution systems must stay operational despite experiencing failures of system parts caused by an attack. Such vital systems can be found on board of other specialised vessel types as well, making robustness of particular interest for them. In general, the risk of a distribution system losing its complete function decreases with increased system robustness.

An improved estimation of the robustness of on-board distribution systems is therefore of utmost importance as it enables a more substantiated trade-off between robustness and other system properties during ship design. It is essential to include robustness explicitly within this trade-off to ensure crew-, passenger- and environmental safety, to increase the possibilities in autonomous shipping and to provide for the integration of sustainable components in the power and propulsion system. The analysis and estimation of system robustness of distribution systems on-board ships in early-stage ship design are therefore at the heart of this study.

1.1. Early-Stage Ship Design

This study focuses on the first two phases: concept design and preliminary design, together called the *early-stage ship design*. This scope is applied because of the design challenges and related design opportunities faced by ship designers during this design stage. Figure 1. shows different representations of a general design process. While the cost and information/problem knowledge graphs show different increasing trends, a rapidly decreasing graph represents the design freedom/influence graph. For this design process models, the design space for a certain problem is at its highest point during early-stage design and decreases rapidly during the early design stage. The challenge lies in the second graph line, the information graph. The known information on the problem and its possible solutions is limited during the early stages; therefore, the most important decisions concerning design direction are to be made with minimal access to information.

1.2. Research Outline

The research motivation provides a ground for a broad range of research topics. Research concerning the improvement of system analyses during early-stage design can be done on process level [2], system level [12] or from a mathematical perspective [13]. Furthermore, the topic that is discussed, robustness of systems, needs not be specific to the application area on which this paper focuses. Robustness is important in other (engineering) sciences as well. This study aims to bridge the gap between the system-level perspective and the mathematical level perspective, which broadly also means bridging the gap between different application areas. At this level of system analysis, a mathematical robustness approach is examined. This method is selected based on its interesting application in telecommunication and power grid research; the application of a more fundamental robustness approach is in line with recommendations by de Vos [10]. This study on the application is divided into three parts: the required assumptions, the resulting adjustments and, finally, the usefulness of the method.

In Section 2., on-board distribution systems are introduced. This includes the used viewpoint within this research, the current robustness approach and the verification set. Section 3. explains the theoretical robustness approach by Van Mieghem [1] and the used graph measures. The applicability of this approach can be found in section 4..

2. Maritime Distribution Systems

Distribution systems are defined as a number of connected components, together transporting a flow (e.a. cooling water, lubrication oil, electricity or data) from a source component via other components to a certain user component. These components are called nodes in a graph representation of the network system; the connections are links or edges within this representation. A system is a physical entity, a network is a model of such an entity, and a graph is a mathematical representation of a network. A distribution system onboard ships can be described using the following generic properties defined by Klein Woud and Stapersma [14]:

- The system contains one or more supply components, such as generators and pumps. In addition, a supplier can be connected to another system with a different type of flow.
- The system moves a particular flow from the suppliers through the system, which happens due to an effort like pressure or voltage. Thus, the system can be modelled like a network in which the flow is distributed.
- The system can contain components in which the flow gets temporarily stored. For example, this can be a tank for fluid systems, while the storage can be batteries in an electric distribution system.
- The system contains users that convert the flow and can be connected to a different distribution system for a particular flow type. The flow can leave the system at the user, or it can be redirected to the supplier side of the system.

In Figure 2., an overview is given of the distribution systems onboard ships. Some system users or systems require different flow types; therefore, they are connected to multiple distribution systems. The onboard distribution systems are analysed using the framework defined by Brefort et al. [12] using three system architectures.

2.1. Brefort Architecture

As mentioned before, this study manoeuvres the gap between the mathematical and system level of distribution system analysis. First, the scope of the system level is defined using a network analysis framework [12]. The main goal of this framework is to provide *'a conceptual method of capturing the key attributes of a distributed ship system ... to describe such a system, ensuring all important aspects are covered ...'* [12]. It is aimed to be a tool in analysing and designing distributed ship systems by increasing the opacity of the interrelations and therefore preventing latent errors. This framework is not limited to distribution systems but to distributed systems, defined as specific types of systems disbursed throughout the vessel.

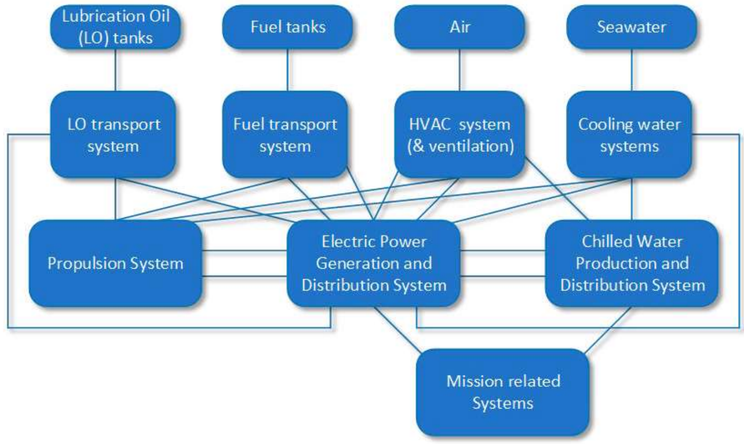

Figure 2. Maritime Distribution Systems and Their Interdependencies [10]

Figure 3. provides a qualitative representation of the different viewpoints used to analyse the distributed system, with a practical example of this framework shown in Figure 4.. The framework is applied to a single distributed system; however, different flows can coexist within this specific sy stem. Subsystems and systems-of-systems have not been included in the framework, nor have relations between different systems.

2.1.1. Physical Architecture

This perspective combines the physical attributes of the ship with the physical attributes of the system components, i.e. what is the ship configuration of spaces and their relationships and where do the system components fit physically. To model a system using this architecture, information on the overall ship configuration and the physical attributes of the main components within the system is required.

2.1.2. Operational Architecture

This time-dependent perspective defines what is required to happen through time to accomplish a given mission. It defines the input and output of the system, including the order in which the system is used and what functions the system is required to fulfil. The human-machine interaction is part of this architecture since it includes the kind and order of the decisions made over time. The temporal operational profile, the functions and requirements through time, must be known to develop this architecture.

2.1.3. Logical Architecture

The connections or links between components within a system are described within the logical architecture. The way the components are connected provides information on the specific service or function a system can fulfil. A system with a number of components can be simultaneously connected in different ways through a specific flow within each subsystem. The (main) components and the connections between these components are required as input for this architecture to be constructed.

2.2. Network Boundary Conditions

Assumptions concerning the definition of a onboard distribution system are mainly based on the network definition by the de Vos [10]. This author analysed maritime distribution systems on system level, using the logical architecture citeBrefort.2018. It is stated that no different modes of operation of a certain system are studied, supporting the approach to model an accumulator as either a supplier or a user. The idea behind this example is emphasised with a more general mention of time, saying that transient behaviour is outside the scope of early-stage system design and therefore outside the scope of the study. Since the temporal

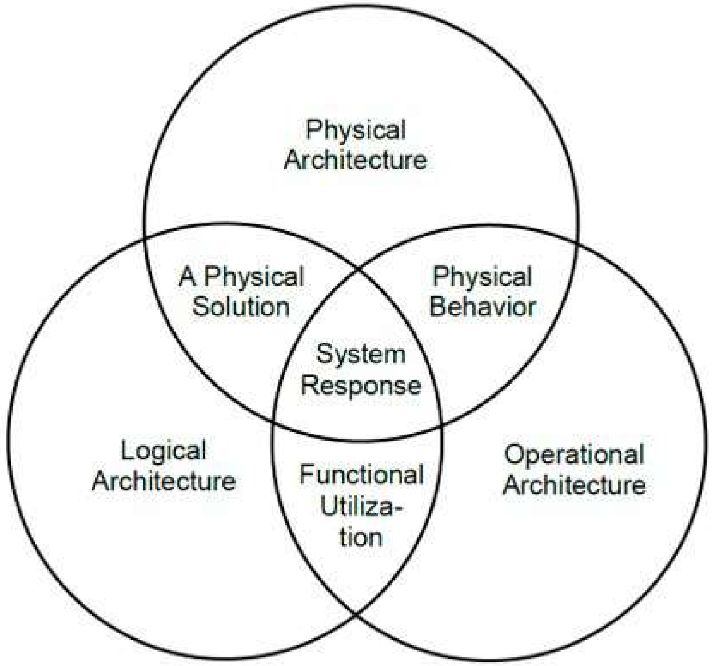

Figure 3. Brefort Architecture [12]

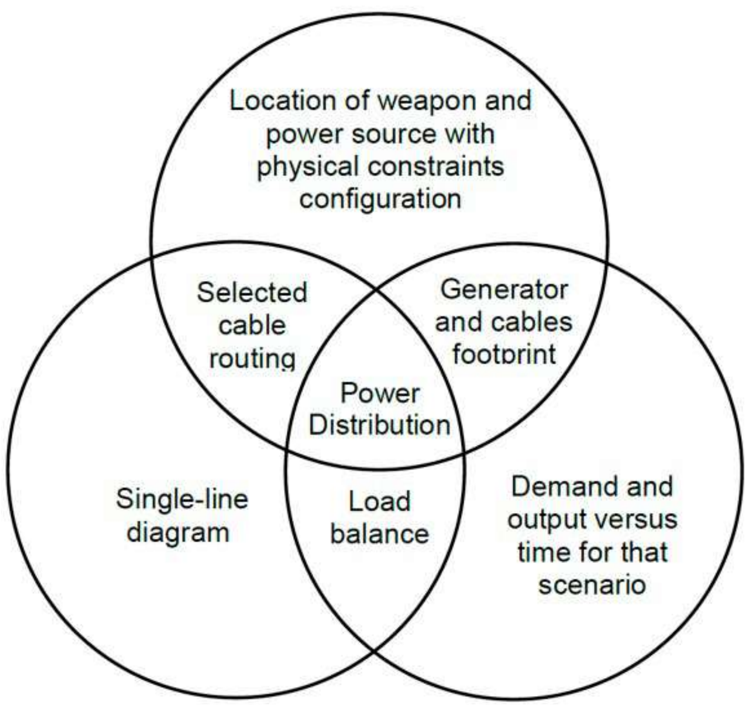

Figure 4. Brefort Architecture Example [12]

information is required to make an analysis based on the operational architecture, this type of architecture, including its overlap, is not included here.

The distribution systems are modelled using three key boundary conditions. The main advantage of having such a concrete application of the theory is that additional assumptions can be made, leading to a less abstract node-edge structure. Apart from these conditions, the previously introduced properties of maritime distribution systems are assumed.

1. A node can be either a supplier or a user in a specific distribution system; these nodes are called converter nodes.

2. Edges are connections of specific distribution systems, i.e. an edge that belongs to a specific distribution system can ”carry” only the specific (predefined) flow type that comes from its suppliers; it cannot distribute any other flow types.

3. When a node is not a converter (i.e. supplier in one and/or user in another specific distribution system), it is a hub in a specific distribution system. Both main pipes and switchboard are assumed to be single nodes in the category hubs. An advance of explicitly stating the existence of hubs in early-stage ship design is that the chances of these hubs being included in preliminary layouts and drawings increases.

2.3. State of the Art Robustness Approach

The ship’s reliability can be improved by improving the reliability of the onboard systems; this improvement can be tackled from different approaches [15], applied as *design rules*. Spruit et al. [16] have distilled ten design rules (rules of thumb) that can be used to improve distribution system survivability:

1. Avoid central distribution systems
2. Separate redundant sources
3. Apply protection if sources must be in each other’s vicinity
4. Separate redundant paths
5. Apply protection where redundant paths have to be close together
6. Arrange feed and return lines for closed-loop systems next to each other
7. Avoid single points of failure
8. Implement a cross-over near the system’s essential users
9. Implement a cross-over near the systems’ sources
10. Combine paths of distribution systems for essential capabilities

These ten design rules can be reduced to three key concepts in improving system robustness: *independent subsystems*, *redundancy* and *reconfigurability* First, *independent subsystems* can be designed within a system, covering design rule 1. If a node or edge of a particular subsystem fails, this does not influence the other subsystems.

The second way of making a system more reliable is including a degree of redundancy in the system, which includes design rules 2 and 4. *Redundancy* is the duplication of specific components or connections, in graph theory called nodes and edges, respectively. The top-level redundancy is full-backup redundancy; the complete functionality of the system stays intact when a component or connection is removed from the system. A system has a lower level of redundancy if it has some functionality loss but does not entirely shut down. *Spatial Redundancy* is contrary to *functional redundancy*, based on the location of the components and connections throughout the ship. If a system is spatial redundant, it remains complete or partial functional when a particular area in the ship suffers damage. For systems, a trade-off has to be made between

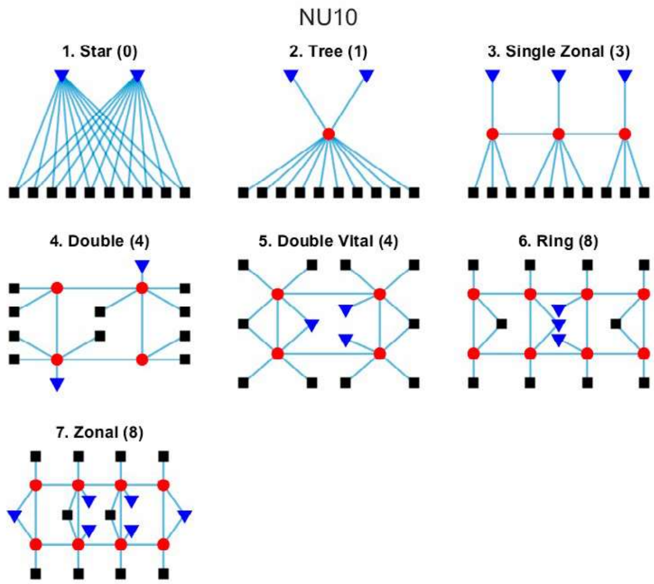

Figure 5. Verification Set I: Undirected Graph with 10 users and varying number of suppliers, hubs and total nodes

spatial and functional redundancy and system claim, on the other hand. The system claim, i.e. the system costs, weight and volume, increase with a higher level of redundancy.

Redundancy is only helpful if the duplicated components or connections can be reconnected to the system. The capacity of a system to connect components or connections in different ways is called *reconfigurability* and represents design rules 7, 8 and 9 . Reconfigurability is the third way of making a system more reliable and depends on the topology of the distribution system.

2.4. Verification Set

The modelled distribution systems are subdivided into five sets of which the properties can be found in Table 1.. The five sets all contain undirected graphs with a varying number of supplier nodes, hub nodes, user nodes and links. The first set is equivalent to an adaptation [10] of network representations by Klein Woud and Stapersma [14], see Figure 5.. According to the design rules, the graphs within a set show an increase in robustness; increase in independent subsystems, redundancy and reconfigurability.

To describe the different sets, certain abbreviations and symbols are used:

- NN number of nodes per graph
- NS number of supplier nodes per graph (**blue triangles**)
- NH number of hub nodes per graph (**red circles**)
- NU number of user nodes per graph (**black squares**)

The sets have been given names based on the most remarkable node properties, for example, Verification Set I or $NU10$ includes a constant number of *user nodes*; the total number of nodes (NN), number of hub nodes (NH) and number of supplier nodes (NS) is variable.

2.4.1. Verification Set V

Set $NH8NS8$ form a deviant set from the previous sets, as seen in Figure 6.. The sets is based on the zonal distribution network, graph 10, of verification set IV ($NU18NS6$). This set has a constant number of supplier, hub and user nodes, only the number of connections between hub nodes is varying. It is assumed

Table 1. Overview node and edge properties verification sets

Verification Set	Directed	NN (number of nodes)	NS (number of suppliers)	NH (number of hubs)	NU (number of users)
Theoretical, [14]	No	Varying	Varying	Varying	Varying
1. NU10, [10]	Yes/No	Varying	Varying	Varying	10
2. NN24	Yes/No	24	Varying	Varying	Varying
3. NN24NS6	Yes/No	24	6	Varying	Varying
4. NU18NS6	Yes/No	Varying	6	Varying	18
5. NH8NS6	Yes/No	32	6	8	18

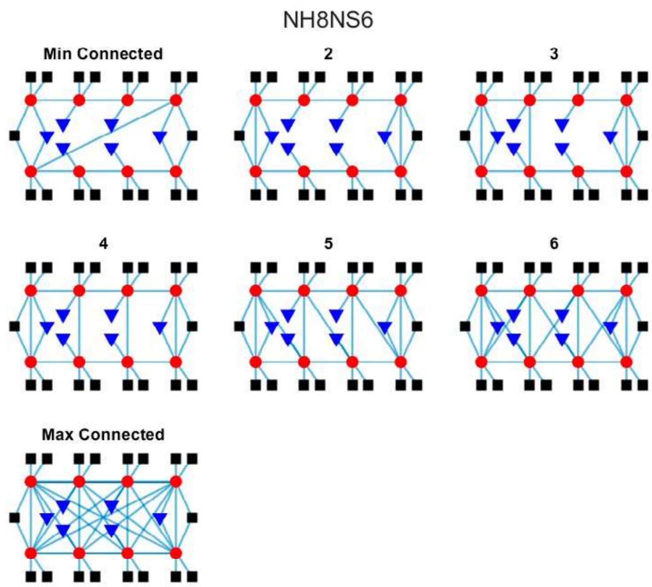

Figure 6. Verification Set V: Undirected Graph with 6 suppliers, 8 hubs, 10 users and 32 total nodes with varying number of connections

that any link added means added reconfigurability and therefore added reliability. The number of graphs in this set is seven, the addition of three extra graphs would provide no additional information and therefore only costs computational power.

3. Robustness Approach R-Value (Van Mieghem)

Several frameworks to improve network robustness have been developed over the last 50 years. The reliability studies focus on the probability of remaining functionality after network component failures, while performance studies focus on higher levels of abstraction to calculate performability. Van Mieghem [1] has developed a framework to calculate network robustness applicable to most network types. The network is defined as a two-layered structure, combining a network topology layer and a service layer, defining the undirected relations between network components and the functions (which may be, and typically are, directed) performed by the network.

The ”goodness” measure or network robustness (*R-value*) is calculated using graph measures combined in a topology vector. The normalised graph measures, such as degree and connectivity, focus exclusively on the network topology and are (very consciously) not meant as service metrics. The selection and weight of the measures is made based on a specific network service; a network providing more than one service has an R-value in which the values per service are combined.

The scope of this framework reaches from physical networks such as power distribution grids, telecommunication networks and pipelines to digital networks like the internet. Therefore, the network is defined in a general and mathematical way. As a result, the networks compared are undirected and only affected by a discrete-time approach. Moreover, when part of a single comparison, the networks have an equal number of nodes without specified functionality. Comparing graphs of equal size is considered good practice within the field of graph theory.

3.1. Network Properties

Any network contains at least two crucial features[1]: the network topology or infrastructure and the service for which the network is designed or created. A service uses the network infrastructure to transport items between two or more nodes. Together with the network topology, the network service makes up the network. The network topology defines how the nodes are interconnected by links and can be represented by a graph with several links and nodes. This framework aims to apply to all kinds of networks, therefore implicitly including distribution systems onboard ships.

According to Van Mieghem [17], the graph representing the network topology consists of a set $\mathcal{N}$ of N nodes and a set $\mathcal{L}$ of L links in which each link connects two different nodes. This implies that the graphs considered are *simple graphs*; they cannot contain multiple edges or loops [18]. A simple undirected graph can be represented by a *symmetric adjacency matrix*, in which only the link existence is specified. Van Mieghem [17] considers the direction of a link as additional information to the usage, and therefore not part of the graph but part of the network service layer. The loss of linearity when including directed links in the topology layer is added as an additional advantage of excluding directionality from the scope by this author. This is in line with the previously mentioned architectures [12], since directed links implicitly have a time dependence: a feature not part of the logical architecture.

3.2. R-Value

The proposed computation of the robustness metric: $R = \sum_{k=1}^{m} s_k t_k$ consists of two vectors of m components. The weight vector s contains m components which reflect the importance of the corresponding values in the topological vector for the service. Therefore, the R-value computed using a specific weight and topology vector is applicable to a single service performed by the network. To compute the total R-value of a network for all services, the R-values per service $R_{S_1}, R_{S_2}, \ldots, R_{S_K}$ are summed with a weight factor per service: $R = w_1 R_{S_1} + w_2 R_{S_2} + \ldots + w_K R_{S_K}$.

The topology vector t contains m components that characterise the topology or graph, such as average hop-count, minimum degree, or algebraic connectivity. Since a high R-value corresponds to high robustness, the components t_k need to reflect this by having a higher value in case of higher robustness.

The constrained model $R_C = 1_{\left\{\cap_{k=1}^{m} t_k \in [t_{\min;k}, t_{\max;k}]\right\}} \sum_{k=1}^{m} s_k t_k$ adds confinements or constraints to the topological metrics. $R_C = R$ if all m considered topological metrics satisfy the minimum and maximum levels. This R_C definition avoids that high values of some topological metrics may compensate unacceptably low values of other topological metrics, still leading to an R-value that passes the overall requirement R_{thresh}.

3.3. Graph Measures

The R-value is a measure for the network "goodness" or robustness. However, it does not have a physical meaning in itself, e.a. it is a measure used to compare different networks and their robustness. On the other hand, the m graph measures within the topology vector t represent a less abstract (sometimes even physical) concept. A selection of graph measures and their physical meaning is described in this section. The physical meaning is focused on the robustness criteria as described in Section 2.3.: independent subsystems, redundancy and reconfigurability. This graph measure collection aims to create and analyse a broad general used field of graph measures but is in no sense a complete or ideal collection of measures, the following graph measures are discussed: degree, connectivity, modularity, eccentricity, cycle basis, and effective resistance.

3.3.1. Degree

The first and most fundamental graph measure is the node degree, for which the local measure (the number incident edges of the node [19]) is reduced to a single global graph measure using the mean value. The network degree distribution or mean degree is related to robustness or reliability because a node with more links can be reconnected in different ways in case of damage or failure. The edge connectivity and the $degree_{hub-hub}$ are similar measures, however, the single point of focus of both measures is different. While the edge connectivity purely focuses on the weakest link, the mean hub-hub degree takes all hub node degrees into account. In case of directed networks, two types of degree can be considered: *in degree and out degree*. The names of these measures are self-explanatory: respectively the number of edges directed to a node and the number of edge originating at a node. The mean value of the in degree and out degree over the total network and over the reduced hub network is identical because all edges begin and end at a certain node.

3.3.2. Connectivity

A distinction can be made between the three types of connectivity. The first connectivity, κ, is a binary value that determines whether a graph is connected $\kappa = 1$ or unconnected $\kappa = 0$. Within a connected graph, as mentioned before, all pairs of nodes are connected by edges through a particular path. The second connectivity is vertex connectivity κ_v; this is the minimum number of nodes that need to be removed from a connected graph to become unconnected. Edge connectivity κ_e follows the same analogy, i.e. the minimum number of edges that have to be removed. Ellens and Kooij [20] state that, in general, a higher node or edge connectivity means a more robust graph. The minimum value within the degree matrix, δ_{min}, can be used to determine the upper bound of the connectivity measure, as shown in equation 1.

$$\kappa_v \leq \kappa_e \leq \delta_{min} \tag{1}$$

Connectivity can also be approached in a probabilistic way, for example, using a *reliability polynomial*. This polynomial $Rel(G)$ is equal to the probability that the graph is connected based on which edges are present. Another probabilistic approach to connectivity is using *degree distribution*. Britton et al. [21] defines $p_k^{(n)}$ as the probability of a randomly chosen node of a set of n nodes to have degree k. With this probability, a probability distribution can be determined: $F = \{p_k; k \geq 0\}$. Complex networks typically have a more heavy-tailed degree distribution, these types of graphs are often referred to as *scale-free graphs* [21].

3.3.3. Modularity

Modularity is a global graph measure representing the extent to which a graph can be divided into clearly separated communities [22]. These separated communities are based on a previously determined community structure. Since this structure is constructed manually, the separated communities can be defined as *independent subsystems*. Currently, one of the main applications of modularity as graph measure is within brain studies, specifically concerning Alzheimer's Disease [23]. Modularity is large when nodes are maximally connected within a subsystem but minimally connected between communities, this value decreases over age and during the advanced stages of the disease. It can be calculated using equation 2 in which E is the number of edges in the graph, A_{ij} the connectivity or adjacency matrix, d_i the degree of a node and δ_{ij} is 1 if the two nodes belong the the same community and 0 otherwise.

$$\frac{1}{E}\sum_{ij}\left[A_{ij} - \frac{d_i d_j}{E}\right]\delta_{ij} \tag{2}$$

3.3.4. Eccentricity

According to Ellens and Kooij [20], the meaning of the diameter and average distance is that a shorter path means a more robust graph. However, backup paths are not considered within this graph measure. In line with this reasoning is the *node eccentricity*, which provides the maximum distance of a given node to

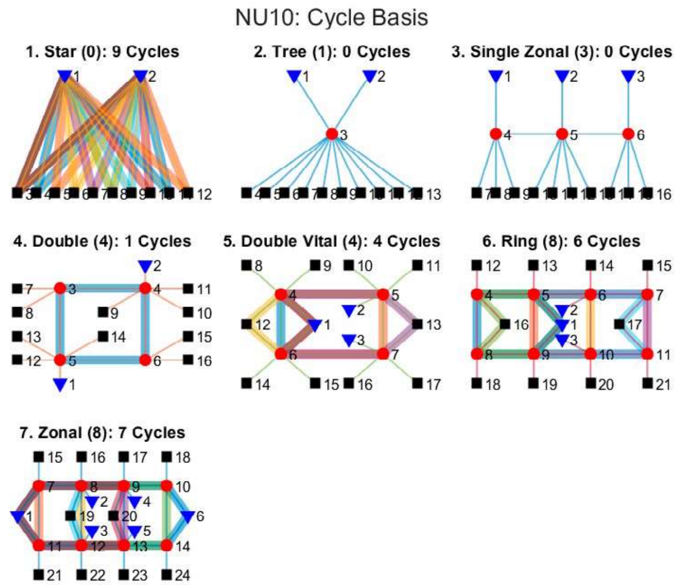

Figure 7. Cycle Bases of Verification Set I: NU10

another node within the connected graph. A more compact network has a higher efficiency and is therefore more robust[20].

3.3.5. Cycle Basis

Cycle Bases are a compact description of the set of all cycles of a graph [24]: the minimal set of cycles making up all cycles in a graph. A cycle is a simple graph or subgraph with as many nodes as edges [19]. The nodes are placed in a way that they form a closed cycle together with the edges. A tree subgraph or graph, on the other hand, is a connected graph that does not contain cycles [25]. The presence of rings or cycles within a network is considered ”good practice” when it comes to reconfigurability and robustness. In Figure 7., some graphs including the present cycles can be found. This figure shows that, in case of undirected graphs, the number of cycles (represented by the cycle basis) is not only dependent on the hub-hub connections, but on the number of connections to supplier and user nodes as well. Therefore, the number of cycles or cycle bases can be used to analyse the redundancy and the reconfigurability within a network.

3.3.6. Effective Resistance

The graph measure *effective resistance* has its origin in the electrical circuits, where resistance is measured in Ohm (Ω). The effective graph resistance or total effective resistance or Kirchhoff index is the sum of the effective resistance over all given pairs of nodes[20]. The resistance decreases when an edge is added to the graph, which means a more robust network. The effective resistance can be calculated using the eigenvalues of the Laplacian matrix. Van Mieghem [1] defines effective graph resistance R_G by equation 3, where μ_k is the kth largest eigenvalue of the Laplacian matrix.

$$R_G = N \sum_{\mu_k > 0}^{N1} \frac{1}{\mu_k} \tag{3}$$

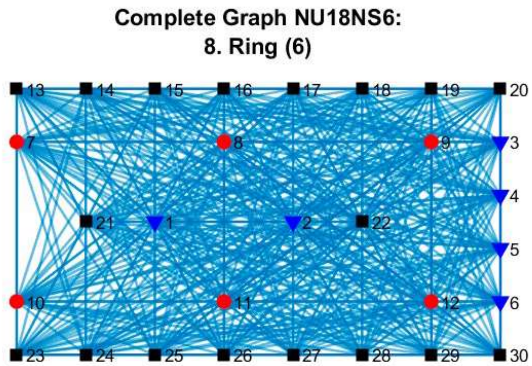

Figure 8. Complete Graph

3.4. Normalisation

The R-value is normalised by taking the q-norm of the weight vector s and the topology vector t. The variable q is a positive integer, usually $q = 1, 2 or \infty$. The q-norm is defined as $\|x\|_q^q = \sum_{k=1}^{m} x_k^q$, in other terms $\|x\|_q = \sqrt[q]{x_1^q + x_2^q + ... + x_m^q}$. If $q = 1$, the q-norm provides the sum of the absolute values in the vector, while a q-norm of $q = 2$ provides the length of the vector. A q-norm of $q = \infty$ gives the largest value of the vector. With a q-norm of $q = 3, ..., \infty - 1$, the largest value of the vector becomes increasingly important with an increasing q-value. This can prove useful but makes the topology constraint values of the constraint model increasingly influential of the R-value. With the q-norm defined, the $\tilde{R}$ can be calculated, which is the unnormalised form of the R-value.

$$|\tilde{R}| \leq \|s\|_q \cdot \|t\|_q \tag{4}$$

from which normalisation follows as

$$0 \leq R = \frac{|s^T t|}{\|s\|_q \cdot \|t\|_q} \leq 1 \tag{5}$$

For this study, the q-norm is set to be 2, which is the "standard" normalisation approach and the Euclidian norm. The separate inputs for the topology vector $|t|$ are the normalised graph measures. To normalise these graph measures, minimum and maximum values must be determined, following the calculation as shown in equation 6. By means of normalising the graph measure values, the normalised value is $0 \leq GM \leq 1$ in which GM is a random graph measure. Therefore, in terms of robustness, the maximum value is considered the highest feasible value a measure can have. The minimum value represents the lowest value for which the graph remains a connected graph. For this determination, two adaptations of the five verification sets are developed: the minimum and maximum connected sets.

$$GM_{norm} = \frac{GM - GM_{min}}{GM_{max} - GM_{min}} \tag{6}$$

3.4.1. Maximum Connected Set

A network that is *maximal connected* is a complete graph. This means that the undirected adjacency matrix A is completely filled, apart from the diagonal. Such a network, as shown in Figure 8., is not considered physically realistic because of the number of connections.

For the maximum connected network used in this example, the number of edges is $(30^2 - 30)/2 = 435$ edges. Moreover, distribution networks as defined by de Vos [10] only contain supplier-hub, hub-hub and hub-user connections (except in case of absence of hub nodes). Therefore, the maximum connected set is defined as equal to the normal set, but with a complete connected hub graph, meaning that all possible

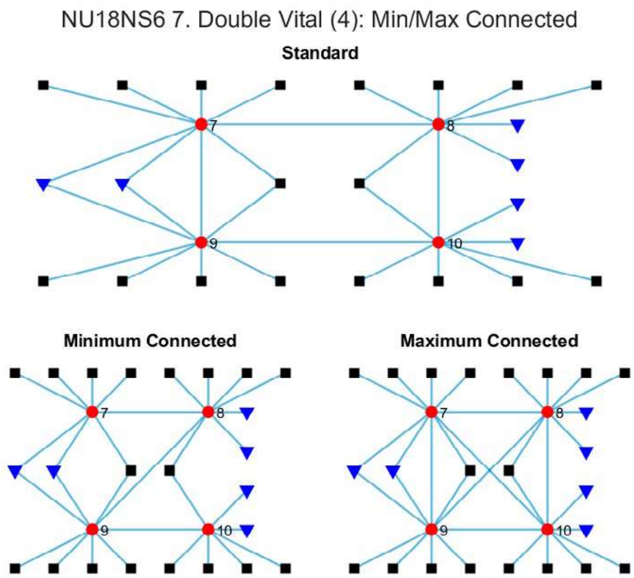

Figure 9. Maximum Connected Hub Graph

hub-hub connections are available. The supplier-hub and hub-user connections remain the same, as shown in Figure 9..

3.4.2. Minimum Connected Set

In the second graph of Figure 9., the *minimum connected set* can be found. In this set, all hubs are connected in through a single path while the supplier-hub and hub-user connections remained the same. This single path means that no ring distribution is possible, however, the set is more arbitrary than the maximum connected set. For example, a network with 4 hub nodes can have a single path through the nodes in the order $7-8-9-10$ or $7-8-10-9$. The first order is applied within these minimum connected sets due to programming reasons, but might not always provide ”the worst” outcome.

3.4.3. Absolute versus Relative Robustness

The determination of the minimum and maximum values relates to the decision what scale to use for the normalisation of the graph measures, and therefore, the robustness. Four commonly known measurement scales are: *nominal, ordinal, interval and ratio scale*. Ascending in the list, more and more information about the data must be available. The nominal scale is literally comparing apples to oranges, while the ordinal scale contains a clear order amongst the possible values (i.e. a service satisfaction query). The difference between the last two scales is that, for the ratio scale, an absolute zero value is known. To normalise the graph measures, the maximum connected and minimum connected hubmatrix are used. Therefore, the normalised graph measures rate along a ratio scale with an arbitrary zero value.

The calculation of the R-value includes additional normalisation to formulate a single robustness measure. In the process of doing so, the maximum and minimum value stay intact, respectively 0 and 1. However, this robustness measure cannot be used on the interval scale because the difference between the values is not known. One can simply state that $R_{G_1} > R_{G_2}$, thus, the R-value can only be measured along an ordinal scale. Despite this limitation, this robustness measure is a composition of a number of crucial robustness aspects and should therefore not be disfavoured over a ratio scaled measure such as failure likeliness.

3.5. Alternative Normalisation

For a network comparison, it is convenient to end up with a single robustness value per graph. The first option to arrive at this point is provided in Section 3.4. using four steps. However, this method is not the sole method to reach a robustness value than can be used to compare different networks.

3.5.1. Un-normalised Graph Measures

A second option to get this single graph is by simply adding up the different graph measures. This figure contains the sum of all graph measures, independent on whether a graph measure represent a more robust graph with a lower or higher value. Despite the clear trend for all verification sets, a star network is robust and the robustness show an upward trend for the other graphs, this figure gives a distorted picture. The distortion is caused by two factors: first, some graph measures represent a more robust graph with a lower value. For example, the node eccentricity and the effective resistance decrease with increasing robustness. Second, the upper and lower limits of the measured values differ significantly. If a measure has values between 0 and 30, it has more influence on the total R-value than a measure with values between -0.5 and 1. Therefore, a third option is defined: a standard normalised robustness value.

3.5.2. Graph Measures Normalised per Set

The third robustness option can been calculated by dividing each graph measure by the norm of the graph measure within the verification set. For example, the mean node eccentricity for the third graph of verification set I ($NU10$) is calculated using equation 7. In doing so, the problem concerning the difference in upper and lower limits has been solved. However, the measures with a lower value for a more robust graph are still represented incorrectly. Moreover, the robustness calculated here is dependent on the used verification set. By adding, removing or changing a graph within a set, the all robustness values is changed because the norm of the graph measures is dependent of the entire set.

$$Ec_{norm}(NU10,3) = \frac{1}{6}\frac{Ec(NU10,3)}{norm(Ec(NU10,all)} \tag{7}$$

3.5.3. Graph Measures Normalised per Graph Measure

The last robustness option is closest to the R-value calculation since both approaches share two main characteristics. First, the robustness value of a specific graph is not dependent on other graphs within the set. Second, all graph measures share the same interval $0 \leq GM \leq 1$ with 1 being the most robust. The main disadvantage of this method is that two high graph measures can compensate for extremely low values of other measures. The R-value calculation prevents the occurrence of such a situation by adding an extra normalisation layer. This layer favours a graph with comparable values for all graph measures over a graph with a topology vector like $[1,1,1,0,0,0]^T$. The calculation of this robustness can be found in equation 8.

$$R_{norm}(NU10,3) = \frac{1}{6}(D_{norm(NU10,3)} + ... + C_{norm(NU10,3)}) \tag{8}$$

4. Applicability

The verification sets previously introduced can be analysed on two levels: the individual graph measures and the combined robustness value. First, values for the individual graph measures, both normalised (using the minimum and maximum connected graphs) and unnormalised values are used.

4.1. Graph Measures Results

The robustness measure showing the six graph measures can be found in Figure 10.. The following trends can be found for verification sets I to IV, more or less dominant for all six graph measures.

- Without the normalisation step, the graph measure shows a step-wise increasing trend.

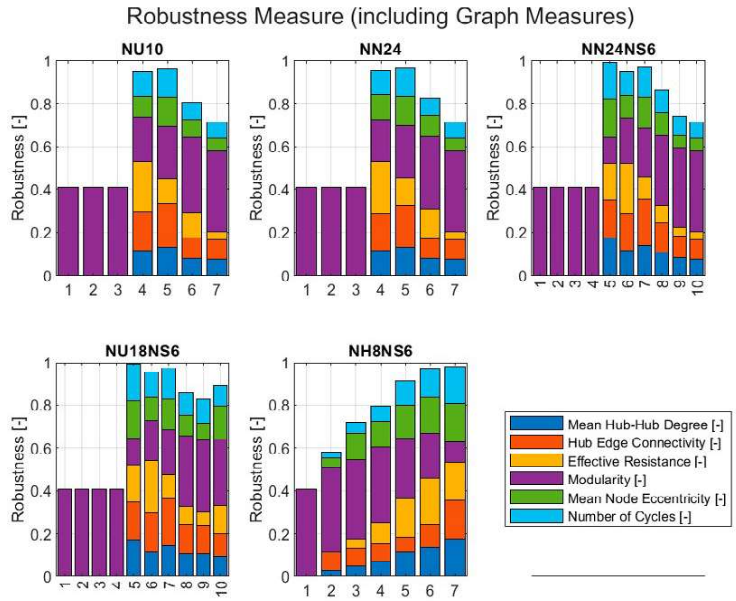

Figure 10. Robustness (incl Graph Measures)

- The values of the measures remain closer to the minimum connected value; the maximum connected value deviates more with an increasing hub-matrix
- Due to the second point, the values of the normalised measure decrease once they contain a value larger than zero. Only amongst graphs with an equal sized hub-matrix, an increasing value can be found.
- The zero values are either adapted NaN values or "real" zero values.

4.2. Robustness Measure Results

Second, the robustness of a set of graphs within five verification sets is analysed. The five sets all contain undirected graphs with a varying number of supplier nodes, hub nodes, user nodes and links. According to the design rules, the graphs within a set show an increase in robustness. The robustness values defined using multiple normalisation approaches can be found in Figure 11..

However, the analysis shows that the normalised R-values do not follow the increasing trend, except for the fifth verification set (with a constant number of supplier nodes, hub nodes and user nodes). This conclusion is limited in its application:

- The normalised graph measures forming the R-value do not follow the intuitive increase in robustness over the verification sets except when the number and function of the nodes within the network remain constant.
- To ensure the intuitive increasing trend, the minimum and maximum values must be constant for a networks within a set.
- The weight vector is not part of the R-value for this verification study, however, the influence of this vector's absence is not part of this study.
- While *unnormalised* and *set-normalised* robustness have been studied, they do not seem to be good alternatives for the actual R-measure.

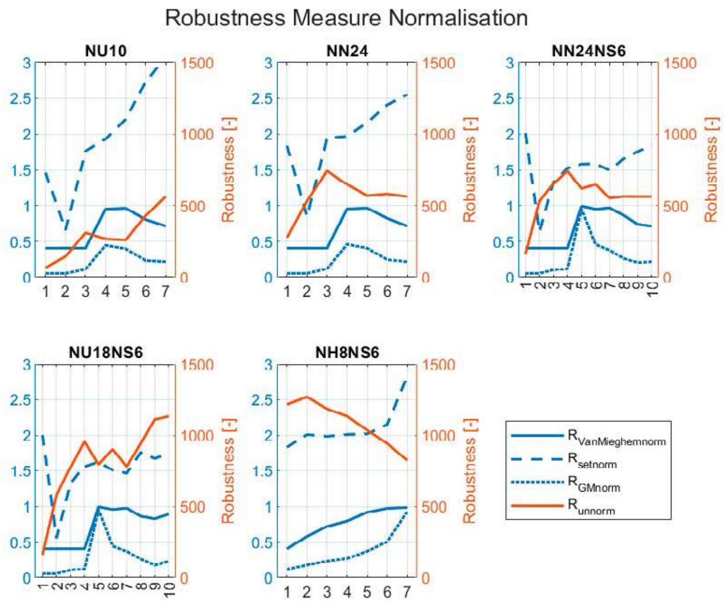

Figure 11. Robustness Normalisation

- Some graph measures provide a measure of the same network property, i.e. hub-edge connectivity and mean hub-hub degree have overlap in calculated values. This effect is disregarded within this study.

5. Reflection

5.1. Limitation

The R-value, as applied within this study, provides an insight in the robustness of on-board distribution systems during early-stage ship design. Suppose the three points of discussion are resolved, one major limitation remains: the number of nodes should remain constant for all compared systems. Moreover, the function of these nodes should be constant as well: a fixed number of suppliers, hubs and users. With the restrictions in allowed connections [10], only a very strongly limited variation scope remains. This scope allows for a proper graph comparison, but the applicability of the R-value is currently still limited within maritime industry.

5.2. Implementation

Despite the challenges in directly using the R-value in early-stage ship design, this study can be applied within the maritime industry in two ways: first, this study provides insight in the measuring approach of different robustness aspects. While a concept such as mean degree or modularity might initially not mean too much to maritime engineers, understanding these graph measures assists in itself in making a trade-off between different system qualities in early-stage ship design. However, not understanding the robustness calculation or the graph measures properly might result in faulty trade-offs leading to unreliable distribution systems.

Second, the long-term application requires comparison between systems with different components and different number of components. In an ideal situation, maritime engineers can use a topology generation tool that generates a topology with the following input: number and type of user components and type and level of required robustness, system claim, operability and sustainability. The output would be a list of five (or so) topologies containing different robustness values and different supplier and hub components. Such a tool can assist in the transition to renewable fuels or more sustainable system components, since the total design space can be explored for each system.

6. Conclusion and Further Research

The goal of this research is to evaluate the applicability of Van Mieghem's robustness approach on distribution systems onboard ships. The first conclusion to address this knowledge gap is clear: the robustness approach by Van Mieghem [1] can be used to perform a robustness estimation of on-board distribution systems in early-stage ship design. Equation 5 shows a generally applicable robustness measure, which can be used to estimate the robustness of any given network within the boundaries of graph theory. Concerning the second part of this question, for the specific application within maritime context, some considerations have been made.

$$0 \leq R_{j,i} = \frac{|s^T t|}{\|s\|_q \cdot \|t\|_q} \leq 15 \tag{9}$$

Van Mieghem [1] does not define which graph measures should be part of the $|t|$-vector within the robustness calculation. The chosen graph measures are assumed to represent the three robustness properties as defined by Klein Woud and Stapersma [14] for distribution systems on-board ships: independent subsystems, redundancy and reconfigurability.

6.1. Weight Vector |s| Definition

As stated, the graph measures are selected based on their indication of certain robustness properties. Dependent on the type of distribution system or the operational profile of said system, the relevant robustness properties change. This change can be expressed using the weight vector $|s|$, which values the used graph measures. Within this study, the weight vector is not studied; for $i = 1, ..., N, s_i = 1$.

6.2. Minimum/Maximum Connected Graph

For the normalisation of the graph measures, the minimum and maximum connected graphs are defined. A subsystem is minimum connected if all nodes are connected with $N-1$ edges; the subgraph containing the hub nodes is assumed to be connected too. The second assumption limits the possible minimum topologies but the number of required edges stays constant. The maximum connected graph is a system with a fully connected hub-graph and two edges connecting each supplier node and user node. All connections are at least duplicated, which can be considered as maximally robust for maritime systems. In other words, all suppliers and users within the maximal connected system are considered vital and should be approached as such.

6.3. Time-Independent Analysis

Within early-stage ship design, the distribution systems are described using a list of main components and a single-line diagram. Therefore, the temporal elements of the R-value analysis are assumed to be out of the scope of this study. The distribution systems are analysed in steady state, providing a single service.

6.4. R-Value Calculation

Due to the normalisation approach of the total R-value, $R = 1$ if all entries in $|t|$ are equal. This means that, if all graph measures are $t_i = 0.5$, the R-value can still have a maximum value. The opposite effect is present as well: if a single graph measure has a deviating value from the other measures, the R-value decreases. The effect is desirable that a negative measure is valued more heavily than a positive measure; engineering practice favours an underestimation over an overestimation. However, a high R-value for comparable, low, graph measures should be avoided at all times. The possible influence of a weight vector in changing or avoiding this effect has not been part of this study.

7. Acknowledgments

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