A STRUCTURED SYSTEMS ENGINEERING APPROACH TO EVALUATE COMPLEX INTER-DEPENDENCIES OF RAPID TRANSIT SYSTEM

NG Zhi Da, CHENG Siew Yen, CHUA Keng Lim, LIM Weng Chiat

ABSTRACT

The Rapid Transit System (RTS) is one of the most common modes of public transport in Singapore with a daily ridership of more than 3 million on average in 2016. The RTS can be viewed as a complex System-of-Systems, with multiple constituent systems interoperating to ensure the smooth delivery of train operations. The emergent behaviour from inter-dependencies across constituent systems may potentially lead to a cascading impact on train operations. This article will share an approach to evaluate the RTS holistically. By modelling the various train systems as a complex integrated network through Optimised Decisions In Network, together with a suite of analytical tools, the study aims to provide a comprehensive and holistic Systems Engineering (SE) approach to quantifying RTS performance, identifying risks areas and enabling evaluation of design options to improve RTS robustness. Future work includes the extension of such an SE approach beyond physical engineering systems to cyber-physical-social dependencies.

Keywords: systems engineering, interdependency, rapid transit system, system-of-systems

INTRODUCTION

The Rapid Transit System (RTS) is one of the most common modes of public transport in Singapore, with a daily average ridership of more than three million in 2016 based on statistics released by the Land Transport Authority (LTA). Any disruption in RTS services may affect a large pool of commuters and hence the reliability of the RTS and its ability to deliver uninterrupted services is critical. Several past disruption incidents, in which a series of cascading failures led to service disruptions, highlight the high degree of complexity of the RTS. One of the recommendations and findings from the Independent Advisory Panel convened by LTA to improve the RTS' robustness in Dec 2015 is that significant improvements can still be made, especially in the identification and management of system inter-dependencies and in mitigating their impact on train operations (LTA, 2016).

The RTS can be viewed as a System-of-Systems (SoS) with a high degree of complexity, with multiple constituent systems (Signalling, Power Supply, Communications, Rolling Stock, etc.) interoperating to ensure the smooth delivery of train operations. The complexity can be attributed to the myriad of inter-dependencies across constituent systems. The emergent behaviour from these inter-dependencies may potentially lead to a cascading impact on train operations due to the failure of seemingly non-critical systems. Therefore, the ability to analyse the RTS holistically and consider the inter-dependencies of systems at various levels through a quantitative and structured approach is key to improving the robustness of the RTS. In addition, for several of the constituent systems, the products or solutions offered by various vendors are vastly different in terms of the architecture and configurations. This reinforces the need to establish the ability to quantify different options and to analyse the trade-offs between them (robustness, availability, reliability, cost, number of equipment, etc).

A study was recently initiated where DSTA collaborated with LTA to provide a comprehensive and holistic systems engineering (SE) approach in quantifying the performance of the RTS, identifying risk areas, and enabling evaluation of design options to improve the robustness of the RTS. The various train systems were modelled as a complex integrated network through Optimised Decisions In Network (ODIN)[1], factoring in functional, logical, system and logistics inter-dependencies. Additional analytical and statistical tools were employed to facilitate the analysis and to glean insights into operational data. This article describes the approach and methodology adopted to evaluate the complex inter-dependencies of the RTS.

RTS DESCRIPTION

The RTS is made up of several subsystems such as Signalling, Power Supply, Communications, Rolling Stock, Platform Screen Door (PSD), Integrated Supervisory Control System (ISCS) interoperating in different operating regions, Operations Control Centre, Depot, Train-borne and Station/Trackside. A high-level representation of a typical driverless RTS system architecture is shown in Figure 1 (Hong, Oh, Yap, & Chan, 2011). The inter-dependencies relating to RTS subsystems are described below.

Inter-dependencies across RTS Subsystems

There are multiple interfaces to other subsystems for each subsystem, as illustrated in Figure 1. In each pair of subsystem interface, several equipment or components from different subsystems connect to each other, creating both functional and logical inter-dependencies. To illustrate, there are broad inter-dependencies between power supply and signalling. The RTS power supply system draws power from the external power grid and steps down the power to provide low voltage power to signalling equipment located in the stations and trackside for daily operations. Similarly, power is also stepped down to rolling stock via traction power and eventually to the train-borne signalling equipment. In a similar manner, signalling can influence power supply through an emergency tripping mechanism, so that operators are able to cut off traction power during emergency or contingency scenarios.

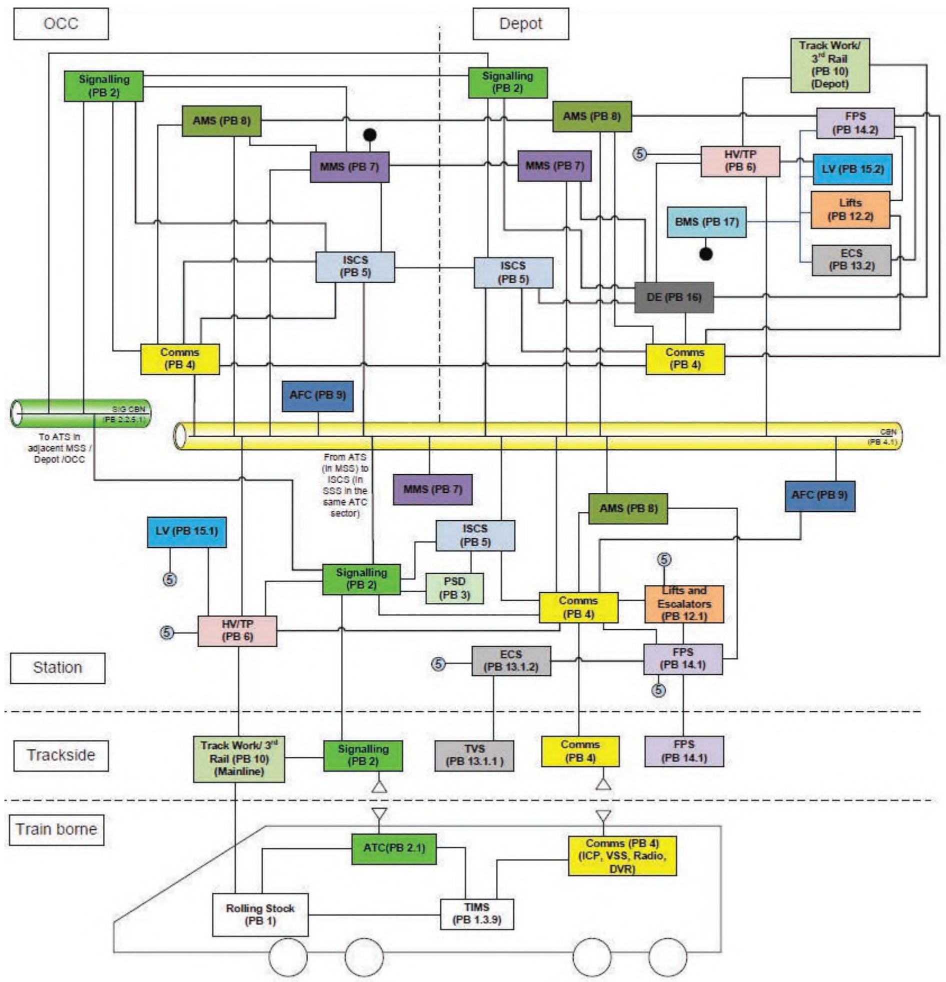

Figure 1. Typical RTS System Architecture (Hong, Oh, Yap, & Chan, 2011)

Inter-dependencies within RTS Subsystems

Within each subsystem, equipment or components are interoperating to support a certain functionality or capability. The complexity of the RTS can be best illustrated using the signalling subsystem, especially with the introduction of Communication Based Train Control (CBTC). The concept of CBTC moves away from the legacy fixed-block signalling concept to a moving-block signalling concept. This allows the headway between trains to be reduced, resulting in the shortening of the time between train intervals and increased train frequency. This inevitably increases the complexity of the signalling systems, requiring tighter integration of different components with an increased number of interfaces. CBTC signalling can be broken down into different components: Computer Based Interlocking that locks and releases train routes; Automatic Train Supervision that monitors and schedules train operations; and Automatic Train Control that governs safe driverless operations and controls bi-directional radio communication between trackside and train-borne equipment. Each of these components needs to communicate with one another constantly to perform their different functions.

Study Objectives

This recent study focuses on the evaluation of the inter-dependencies across two RTS subsystems. Through the evaluation, the study aims to draw out the risk areas or emergent behaviours arising from these inter-dependencies that can potentially lead to cascading impacts affecting the entire RTS line.

Using the same approach, the study also looks into the comparison of various distinct architectures for one of the RTS subsystems. As the architectures supplied by various vendors for this subsystem are distinctly different, compounded by its complex nature, it is challenging for decision makers to evaluate the strengths and weakness of various aspects, such as robustness and availability, without a quantitative approach. Therefore, this study aims to overcome this challenge by providing a quantitative means of evaluating trade-offs.

MODELLING COMPLEX INTER-DEPENDENCIES

Vulnerability assessment of networks is one well-researched domain that assesses the impact of targeted or random infrastructure component failures with considerations for inter-dependencies. Commonly, modelling approaches such as Leontief input-output based models or agent-based models are used (Pant, Hall, & Blainey, 2016). However, it is observed that such approaches seldom take into consideration the reliability aspect of systems that influence the operational state of the nodes or systems, which is critical to this study's context. To the best of our knowledge, there is no existing framework or tool, except for the systems engineering tool called ODIN, that is able to evaluate vulnerability of large scale complex networks, taking into account the reliability of individual systems.

ODIN was developed by DSTA to enable planning for network-centric military operations (Cheng & Seah, 2014). Although initially designed for military context, ODIN is equally applicable for complex SoS such as the RTS, as the fundamentals of analysing interconnected systems remain the same. ODIN was developed with the ability to simulate complex network systems while incorporating systems reliability, operational profiles and maintenance support concepts. This tool enables the quantification of inter-dependency and inter-connectivity across component systems. With the means to quantify, ODIN enables one to identify weak links and key drivers for unavailability in complex networks.

The recent study utilised two main engines of the ODIN tool – the process simulation engine and the network-search computation engine. The process simulation engine adopts a discrete event Monte Carlo simulation method to evaluate dynamics and stochastic system failures, logistics supply chain, repair process and operational profiles. The network search computation engine adopts path-searching techniques to compute and evaluate inter-dependency across networked systems.

There are numerous metrics that evaluate the importance of the nodes or links within a network. One example is the Centrality measurement used in social network analysis to measure the influence of a person, and Page Rank used by Google Search for the ranking of websites in search engine results as a form of importance of websites. In a recent survey to review and compare the various metrics (Alenazi & Sterbenz, 2015), it was concluded that there is no single unique graph metric that can capture both robustness and interconnectivity. Nevertheless, cognisant of the limitation, ODIN has introduced an in-built feature to measure network criticality as a spectral graph metric, to facilitate the analysis of robustness at the system and network level.

In ODIN, for the purpose of drawing out the degree of criticality or how dependent the overall mission is on a specific node or system, network criticality factor (CF) is used to define the robustness at the system level. The CF is defined as the ratio of the number of paths that need to transverse that specific system, relative to total number of paths available end-to-end from source node to sink node, as defined in the mission context. A value of CF which equals to 1 indicates a bottleneck or single point of failure, while a value of CF which equals to 0 indicates that the mission is independent of the system operational state. By automating the computation of CF for every system node, one is able to conduct quick analysis and review the importance of each system node in relation to the defined mission.

At the network level, CF can also be used to determine possible combinatorial failures. Making use of the combat damage feature in ODIN, each system in the network is deliberately brought down to assess the impact of failure to the CF of the remaining systems. If the CF of any other system is elevated to a value of 1, it implies that a new single point of failure is formed. This also means that failures of both systems concurrently will cause a service disruption. Through this mechanism, an exhaustive list of combinatorial failures can be generated. For a large-scale complex network, it is near impossible and very inefficient to analyse and generate such a list manually through rationalisation.

One key advantage of ODIN is its scalability, which is enabled by its ability to measure the end-to-end availabilities of interconnected system matrices (Cheng & Seah, 2014). This is an extension of an analysis of typical system level availability, and it allows the flexibility to measure the end-to-end availability of any pair of systems-systems, or subnetworks, and the overall mission network availability. This is essential for the analysis of complex networks, where there is a need to break down systems into smaller and manageable subnetworks or subsystems to identify weak links.

The usage of ODIN is assessed to be fitting in the context of evaluating and quantifying RTS to identify vulnerabilities or weak links. ODIN is able to consider the operational profile of the RTS (service operations and engineering hours), reliability of systems (down to the equipment level), and the factoring of inter-dependencies at various levels, i.e. *between* subsystems level and *within* subsystems level. This article describes the use of ODIN as the primary tool, complemented by a suite of analytical and statistical techniques, to represent and quantify the complex inter-dependencies of the RTS.

PROPOSED FRAMEWORK AND APPROACH

For the realisation of a holistic and implementable framework to support the structured evaluation of complex systems, it is clear that a multi-disciplinary approach or combination of techniques is required. In the proposed approach, it centred on adopting graph theory or network analysis as the key foundation, augmented by a suite of statistical and analytics tools for a comprehensive assessment, as shown in Figure 2.

One key element of the approach is the definition of mission effectiveness, as this will affect how operational impact is quantified and subsequently influence how trade-off analyses are evaluated. Drawing parallels from military applications, the approach taken considers the complex network as a closed-network first, without factoring in external threat conditions.

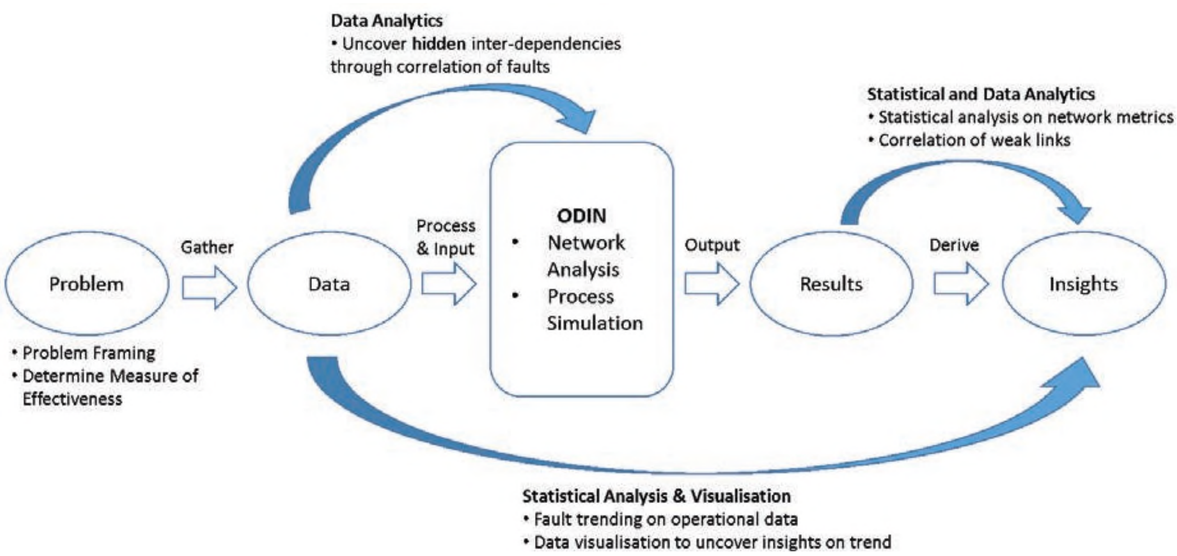

Figure 2. Proposed framework and approach

The next step is to capture and evaluate the inter-dependencies of systems, and to identify risk areas. Further assessment can then be made to assess what are the potential failure modes or possible external threats (e.g. cyber threats) that can bring down the critical node(s). This can help planners make more informed decisions on how to prioritise resources or introduce mitigating measures.

APPLICATION TO RTS

Determining the Measure of Effectiveness

A typical Measure of Effectiveness (MOE) used in the railway industry is Mean Kilometre between Failure (MKBF) for disruption of more than five minutes, in which regulators and operators are actively tracking. This MOE tracks the reliability performance of the entire RTS line for regulatory monitoring purposes, considering factors such as train frequency and the length of the RTS line. In the recent study, two other MOEs namely, (a) Availability and (b) Number of Service-affecting Disruptions (of any duration), are chosen for the following reasons. First, the analysis is only for two of the subsystems, and will not be representative of the entire line MKBF performance. Second, most of the systems studied are operational 24/7 and are independent of factors such as length of RTS line, and frequency of trains, which are accounted in MKBF computation. Thus, availability and disruption rate are assessed to be more suited for the intended study outcomes, as it allows a more direct comparison between subsystems, and ease the identification of weak links.

Data: Processing of System Data for inputs to ODIN

One of the key parameters of ODIN is the system reliability data or the equipment Mean Time Between Failure (MTBF). This system data can typically be extracted from two sources – Original Equipment Manufacturer (OEM) data and field data. Field data is preferred over OEM data, as field data is more reflective of the operating profile and actual operating environment. However, one should be careful when computing field MTBF before concluding that the field data is representative of the true MTBF. It is very risky to use the field data if it is based on just one registered failure. Thus, statistical Chi-square hypothesis testing is carried out for each equipment to calculate a two-sided confidence interval for the set of test (field) data based on a time-truncated test. If the OEM MTBF falls within the intervals, it is then used as the MTBF to be entered into the ODIN model. Otherwise, the field MTBF is used here (Anthony, 1999),

$$MTBF_{LowerLimit} = \frac{2T}{X^2\left(\frac{\alpha}{2}, 2n+2\right)}; \qquad MTBF_{UpperLimit} = \frac{2T}{X^2\left(1-\frac{\alpha}{2}, 2n\right)}$$

where: T is the accumulated amount of operating life;
n is the observed number of failures;
X^2 is the value of the random variable having chi-square distribution, with a significance level α , and degrees of freedom 2n+2 (lower limit) and 2n (upper limit).

Data: Glean Insights through Analysis of Reliability Data

Besides determination of the equipment field MTBF, the operational data collected is a valuable source of information in which meaningful insights, such as equipment failure trends, can be gleaned. There is much potential in this area of reliability data analysis, where data analytics and statistical techniques can be employed to sieve out insights such as finding correlations between faults or identifying equipment with increasing failure trends. Further investigation can be conducted for equipment with increasing failure trends to uncover the root cause and prevent it from escalating to a service-affecting disruption. The deviation of expected equipment failures and actual failures can also be compared for optimal spares provisioning purposes. Failure trending by location/stations or by fault types may provide some insights into potential weak areas. As the data is multi-dimensional, a data visualisation tool such as *QlikSense* © or *Tableau* © will be useful in uncovering any hidden trends as illustrated in Figure 3.

Data: Mapping of Inter-dependencies

In general, inter-dependencies between the physical engineering systems can be categorised into three types of inter-dependencies: (a) Logical Inter-dependencies; (b) Functional Inter-dependencies; and (c) Geographical Inter-dependencies as shown in Table 1.

Inter-dependencies	Definition
Logical	Refers to systems having direct physical connections.
Functional	Refers to systems that need to work together to support a specific operation without the need to be physically connected.
Geographical	Refers to systems that are co-located together.

Table 1. Logical, functional and geographical inter-dependencies

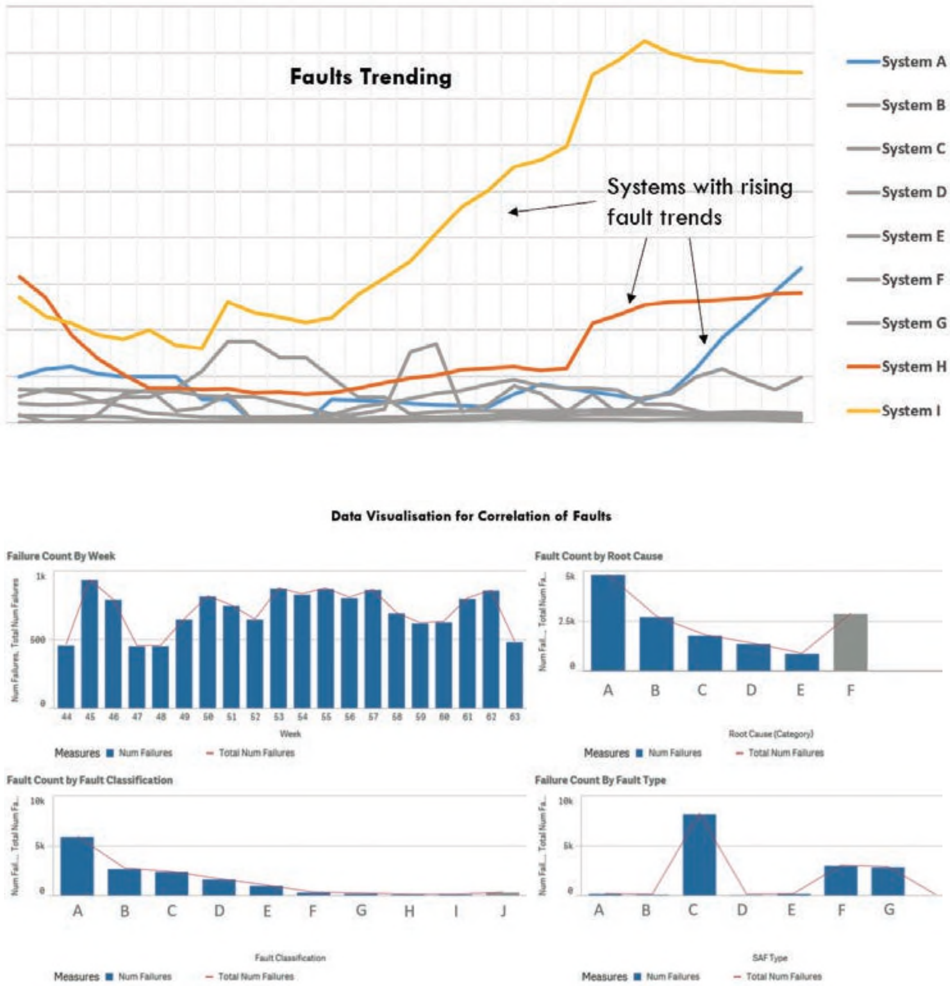

Figure 3. Illustration of reliability data analysis (Indicative)

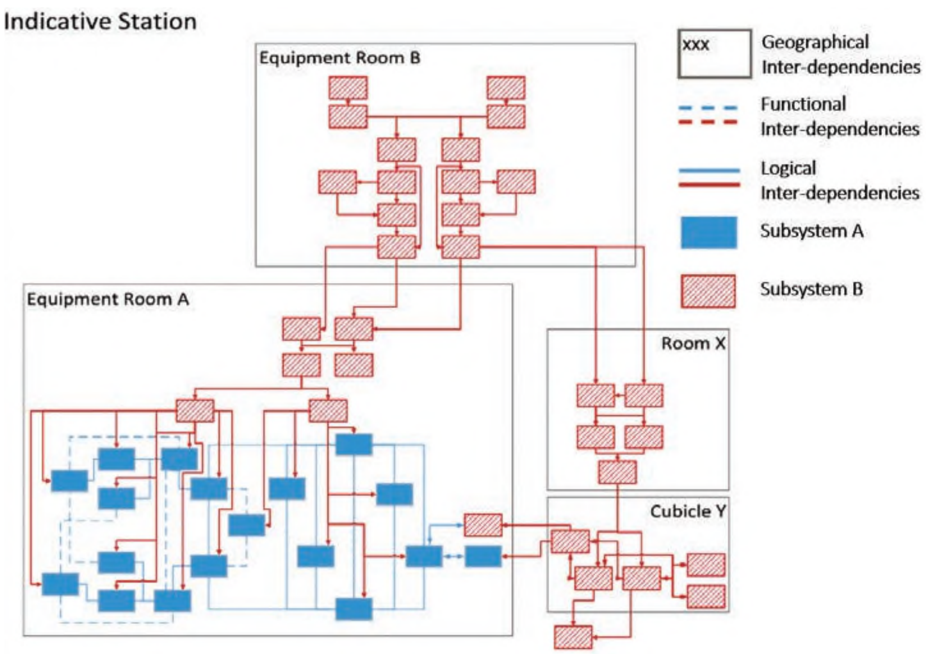

Figure 4. Mapping of inter-dependencies across RTS (Indicative)

The mapping and determining of inter-dependencies, as shown in Figure 4, is one of the more challenging yet more critical tasks. Being able to determine all inter-dependencies enables the capturing of emergent behaviour upon the failure of certain systems. Most inter-dependencies are reflected in design documents via physical interconnectivities, functionalities and failure consequences documents. However, there is a risk that not all inter-dependencies will be captured, and this highlights the importance of employing data analytics techniques such as clustering to sieve out hidden inter-dependencies by analysing operational failure data. Uncovering hidden inter-dependencies previously not known to operators, project teams or domain experts is critical, as these might be failure scenarios that were not initially thought through with no mitigating measures catered for.

Analysis of Results to Derive Insights

With the completion of the inputs collection and simulation phase, the raw output of ODIN can be extracted in three folds: (a) Availability of systems and pre-defined missions or operations; (b) failure rate of systems or number of disruptions; and (c) network criticality factor (CF) of individual systems. From the raw results, one can already identify weak areas and the corresponding key drivers of unavailability. Addressing these key drivers will reap the highest improvement in availability. Bottlenecks can also be sieved out through the generated network criticality metrics to identify systems that have CF which equals to one.

Statistical and data analytics techniques can be applied to the raw results to distil valuable insights into the RTS. ODIN allows the output of the end-to-end availability matrix for all system-to-systems at various levels (entire network or subnetwork). By applying correlation techniques, one can identify systems that are closely linked to the weak areas (at various levels) and are possibly indirectly contributing to the lower availability. Additional statistical analysis is required to compute the likelihood of combinatorial failures as not all combinatorial failures will be reflected in the Monte Carlo simulation results; notably for systems with relatively higher MTBF, they are unlikely to see concurrent double failure. However, the impact might be high, and it is of interest to highlight high impact-low likelihood scenarios to present a comprehensive risk picture. When comparing between network architectures, further correlations can be done using analytics to identify commonality in weak areas and more importantly draw out the strengths and weaknesses of each design.

OUTCOME AND TAKEAWAYS

This study applied the framework and approach successfully by quantifying the expected availability, factoring in the functional, logical and logistics inter-dependencies across the two RTS subsystems examined. The study identified the key drivers of unavailability and bottlenecks, so that the areas where more attention should be given to can be narrowed down for the development of mitigating measures or potential design enhancements. Not all stations or equipment are of equal importance, and a comprehensive list of criticality factors generated across all equipment and stations provided a means to prioritise maintenance or recovery effort within limited engineering hours. The same list can also be used as additional consideration to support asset renewal prioritisation.

Often, combinatorial failures with cascading impacts are a result of faults across multiple system types and not just within the constituent system. The risk matrix of potential combinatorial failures, ranked by impact and likelihood, as illustrated in Figure 5, can help planners/operators develop mitigating measures for high impact and high-likelihood scenarios.

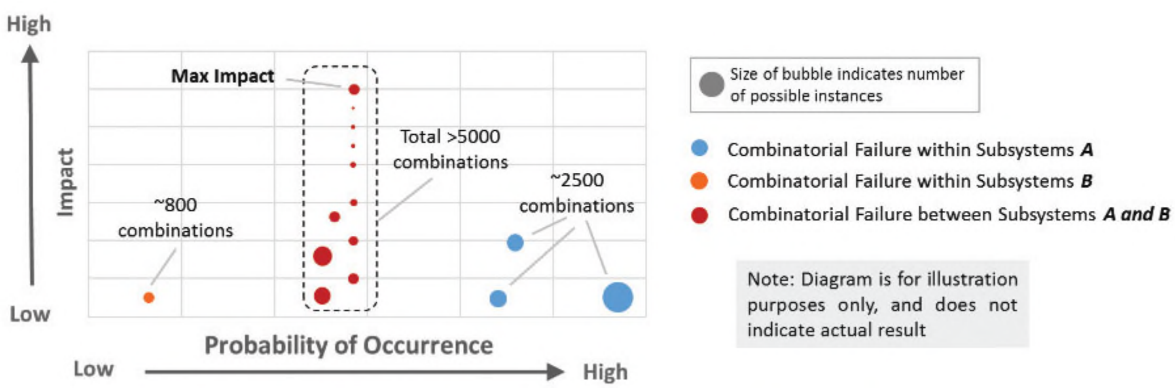

Figure 5. Risk matrix of potential combinatorial failures (Indicative)

Such a structured and quantifiable evaluation approach provided a scientific and objective perspective to draw out strengths and weaknesses of various architectures and component configurations, by examining from multiple dimensions such as robustness and reliability. The analysis outcome can help planners to influence and shape future tender requirements.

Essentially, the team successfully validated the structured approach for the modelling of complex RTS inter-dependencies, which can be extended to future RTS lines.

OTHER CASE STUDIES

The above described framework and approach has also been successfully applied to military airbases, where the mission was defined as the ability to support a full range of airbase operations, such as launch and recovery of aircraft and physical security. This allowed for the holistic management of the airbase to determine the optimal target of each system and to assess the impact of any system failure for the airbase operations as a whole. The study mapped out inter-dependencies across the systems required to support the airbase operations, ranging from the launch and recovery of aircraft (e.g. landing aids, navigation aids) to physical security systems (e.g. perimeter surveillance). One essential component is the dependency of mission critical systems on critical infrastructure (e.g. power, network, water). An indicative illustration of inter-dependencies across some of the key components can be seen in Figure 6. This study covered more than 50 system types and over a thousand nodes. The outcome of the study is the integrated management of the airbase to enable resource prioritisation. In a similar context, such SoS management of military airbases can be extended to civilian airport operations.

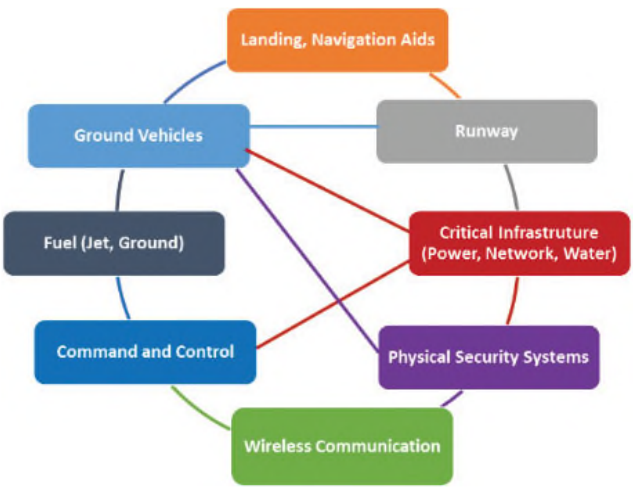

Figure 6. Inter-dependencies in airbase operations (Indicative)

POTENTIAL FUTURE WORK

The recent study focuses on the inter-dependencies between two RTS subsystems. With the completion of the study, potential work could be the extension of the study to all critical RTS subsystems (i.e. Signalling, Power Supply, Communications, ISCS and Rolling Stock) that could potentially affect service operations. One of the key challenges of evaluating all critical RTS subsystems is that the number of inter-dependencies increases exponentially with the addition of each subsystem. To overcome this, future work should leverage existing models that have been built and include the additional inter-dependencies, which have been assessed to be feasible. The key intention is to consider the RTS more comprehensively, with the aim of improving the robustness of train operations.

From another angle, with the rapid proliferation of Internet-of-Things together with a series of Smart Nation initiatives to provide real-time data monitoring and feedback loops, inter-connectivity between systems is no longer bound by physical aspects. Interactions of cyber and social (e.g. human, organisation, workflow) aspects with physical engineering systems have become critical in presenting new forms of vulnerabilities, and another dimension of potential operational impact. Future work will embark on extending inter-dependencies beyond physical engineering systems to cover more holistically cyber-physical-social (CPS) aspects to derive a new systems engineering approach to address these emerging technological trends and their potential impact. Many researchers have already embarked on this journey to examine CPS, and this inspires the team to build on the current work to advance in the area of CPS.

CONCLUSION

In conclusion, an SE approach is essential in evaluating large-scale complex systems such as the RTS. ODIN was initially an SE tool that DSTA developed to support the military on complex networked capability design and realisation. When augmented with statistics and data analytics techniques, ODIN proves to be a suitable approach for modelling the complex inter-dependencies of the RTS. In this article, an SE approach was presented, of how ODIN together with statistical and analytical methods can be used to uncover insights, helping planners or operators on improving the robustness of train operations. Such an SE approach could be adapted and adopted for complex systems beyond physical engineering systems to consider cyber-physical-social dependencies.

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ENDNOTES

[1] ODIN is a DSTA in-house developed tool to simulate and quantify complex network systems while incorporating systems reliability, operational profiles and maintenance support concepts.

BIOGRAPHY

NG Zhi Da is a Principal Analyst (DSTA Masterplanning and Systems Architecting) and is currently involved in Air Force related Operations Research studies. He obtained a Bachelor of Engineering (Industrial and Systems Engineering) degree with Honours from National University of Singapore (NUS) in 2010.

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