17TH ANNUAL ACQUISITION RESEARCH SYMPOSIUM

System-of-Systems Acquisition Analytics Using Machine Learning Techniques

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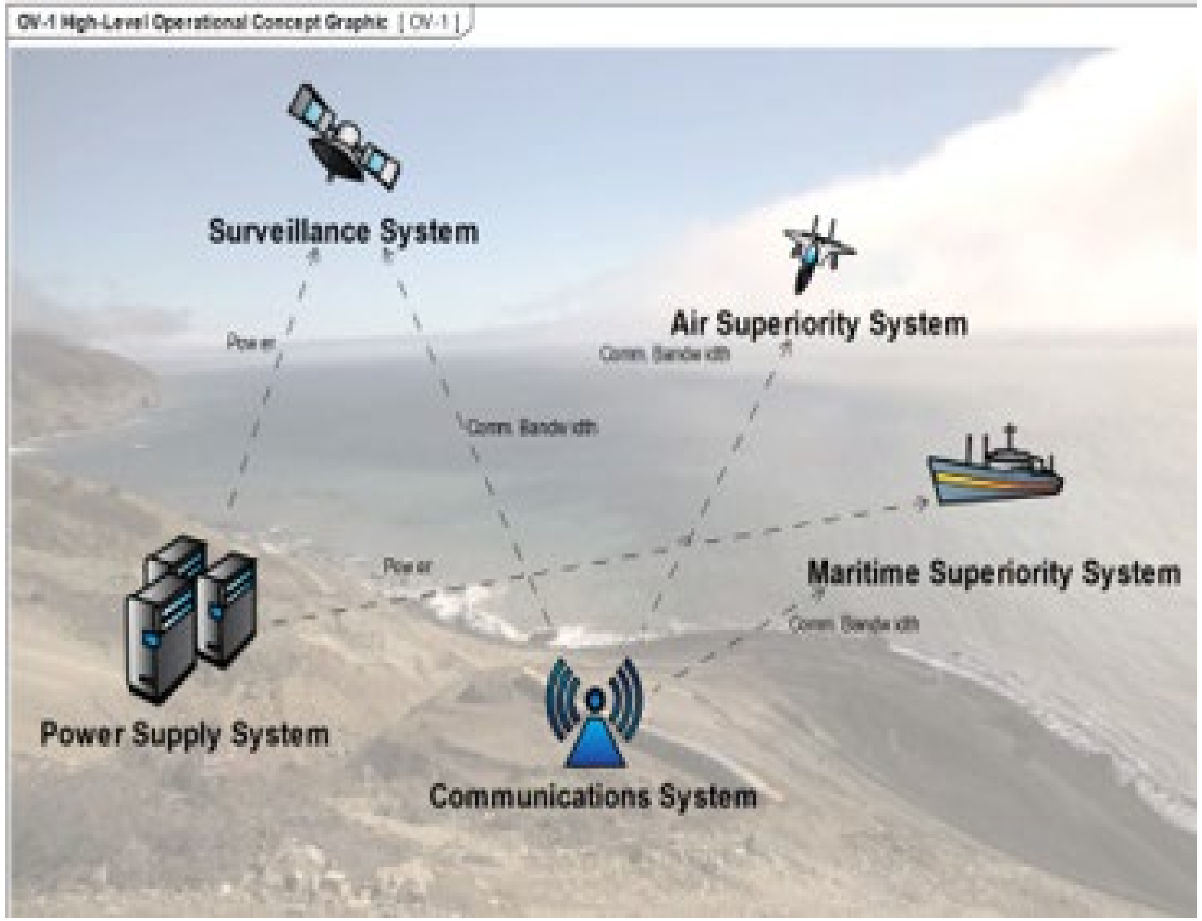


Department of Defense Architecture Framework (DoDAF) OV-1 representation

Motivation

“Most acquisitions for complex systems are done at the system level and independent of other systems in the architecture. Any organization acquiring a complex system employs some form of data analytics to assess a system’s independent objectives. Even though the systems contribute to and benefit from the larger SoS, the data analytics and decision-making about the independent system is rarely shared across the SoS stakeholders…”

Problem Statement

Identify how the sharing of datasets and the corresponding analytics among SoS stakeholders can lead to an improved SoS capability

STATUS QUO

- *Predictive data* analytics provides an ability to anticipate and predict outcomes by collecting and utilizing prior information (Waller & Fawcett, 2013) (Rehman et al., 2016) (Joseph & Johnson, 2013).
  - *Using data to guide decision-making has been around since the* ***Babylonian times****, where data was recorded on tablets to predict harvest (Lo & Hasanhodzic, 2011).*

- In 1940s, with the advent of computer development, the ability to reason over large amount of data emerged. Using computational data to analyse has occurred in three waves since then:
  - Analytics 1.0 – data-based decision making
  - Analytics 2.0 – handle large structured and unstructured data sets
  - Analytics 3.0 – big data landscape shaped by the volume, variety, velocity, and veracity of data

- For SoS acquisition, **Analytics 3.0** provides a unique challenge where the individual organizations contributing the constituent systems individually employ a suite of unique predictive and prescriptive analytics tools.

- Capabilities of computing and **machine learning** techniques are evolving in the Big Data landscape
  - How can we leverage these techniques for SoS acquisitions?

- Analytics and the underlying data sets are rarely shared across the SoS stakeholders
  - Yet SoS capability emerges from the **collaboration** of otherwise independent systems

MACHINE LEARNING – REVIEW

- Supervised learning use predictors and a target variable to learn a function that maps the predictors to the target
- Unsupervised learning algorithms model underlying structure of data with a set of predictors and no target variable
- Machine Learning techniques are finding numerous application in various domains

Method	Description	DoD Application
Linear regression	Fits predictors and response to regression line using OLS	Two-step process to identify DoD programs that have cost growth using logistic regression and estimate the cost growth of those programs using multivariate linear regression
Ridge and Lasso regression	Regularization methods used when the standard linear regression model suffers from multicollinearity and overfitting	Ridge: address multicollinearity problem in defense spending by modeling relationship between military expenditures and economic growth Lasso: variable reduction technique to select variables most relevant to supply and demand of airline tickets
Binary logistic regression	Models the log odds of a binary categorical outcome as a linear combination of quantitative and/or predictors	Explore how the DoD can use info on contractor performance to identify variables that drive success of a contract
Support vector machines (SVM)	Uses a linearly separable hyperplane to classify data into two classes	Estimate the state of charge of lithium-ion batteries for unmanned aerial vehicles
Artificial neural networks (ANN)	Model consisting of interconnected nodes that receive inputs and return outputs based on an activation function	Detect anomalies in engine operation of advanced military aircraft
K-nearest neighbors	Classifies data points based on the class that appears the most among neighboring points	Classify types of military vehicles based on the acoustic and seismic signals generated
Naïve Bayes classifier	Uses Bayes theorem to calculated probabilities of a class response and selects the class with the highest probability as the output	Identify DoD acquisition programs with elevated levels of cost risk
Decision Tree	Algorithm that recursively and iteratively partitions the data into homogeneous subsets to identify a target outcome	Use of a decision tree to analyze success and failure of a contract
K-means	Use to identify homogeneous clusters in a data set	Uncover patterns in military peacekeeping documents

PREVIOUS WORK

- Conceptual problem to demonstrate the impact that even small, intuitive changes in how data is collected and shared, can result in different predictive and prescriptive analytic implementations and lead to a different outcome for **SoS decision making** (Davendralingam et al., 2018).

- For example (in figure), a Market Research Team performs a **market study** to understand the consumer's opinion
→ this information can be used to support the *future* product design by providing insights on what aspects are the most crucial for the consumer
→ resulting in better understanding of **information flow**
→ collected **data** can then help dictate demand and thus control profit

- In this research, we are pursuing development of a framework that will facilitate identification of such links and quantify how the **SoS level capability** could evolve by **sharing data** sets across the systems.

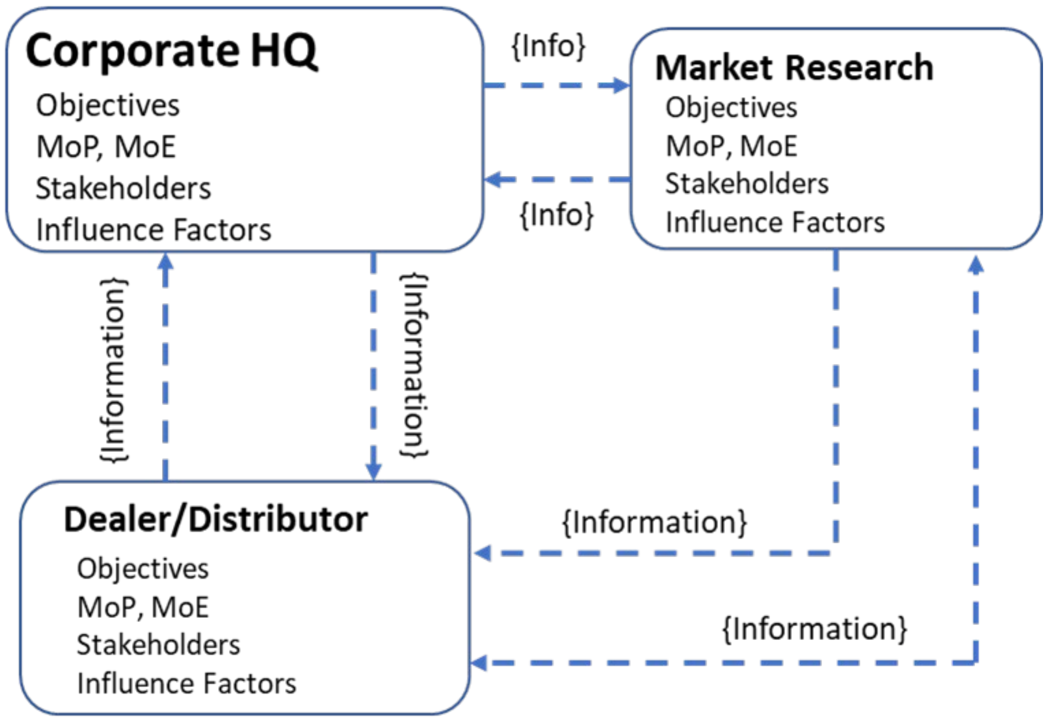


Figure: Conceptual problem to identify impact of data-set connectivity

SOS ACQUISITION PROBLEM & CASE STUDY

SoS Acquisition Problem

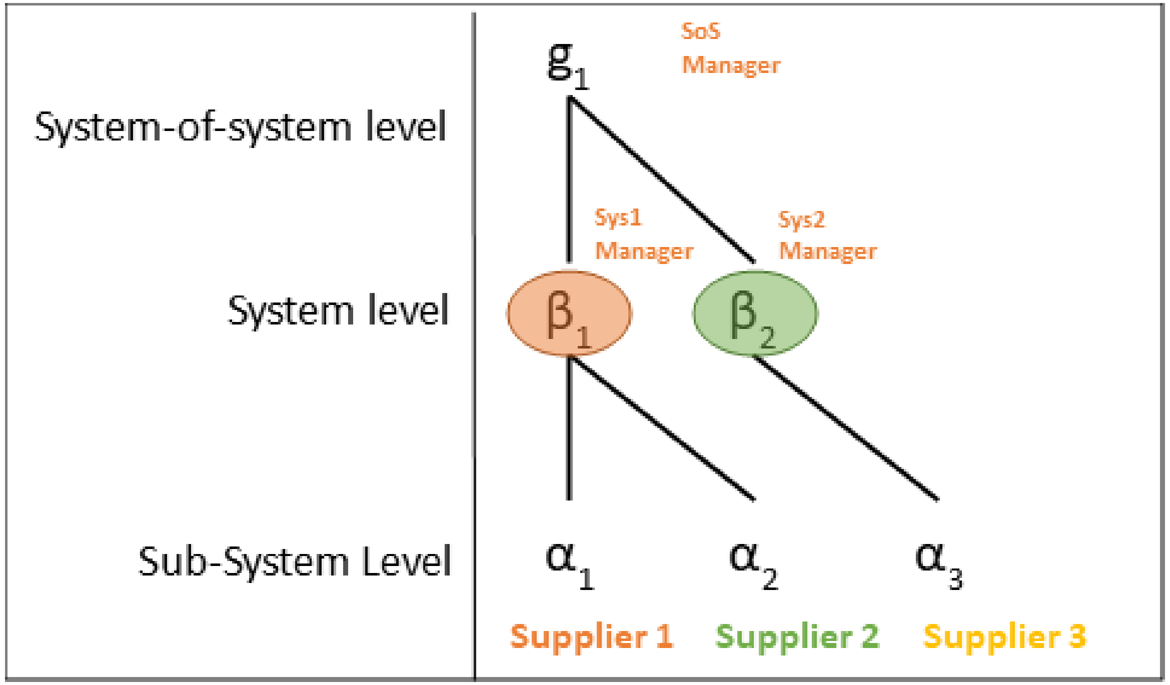
- Approach to lexicon and taxonomy for representing the various SoS constructs are derived from Davendralingam et al., 2018.

- Here, sub-systems α_1 and α_2 form the system β_1 whereas α_3 relates to the system, β_2. At the higher level, β_1 and β_2 form the system-of-system, γ_1.

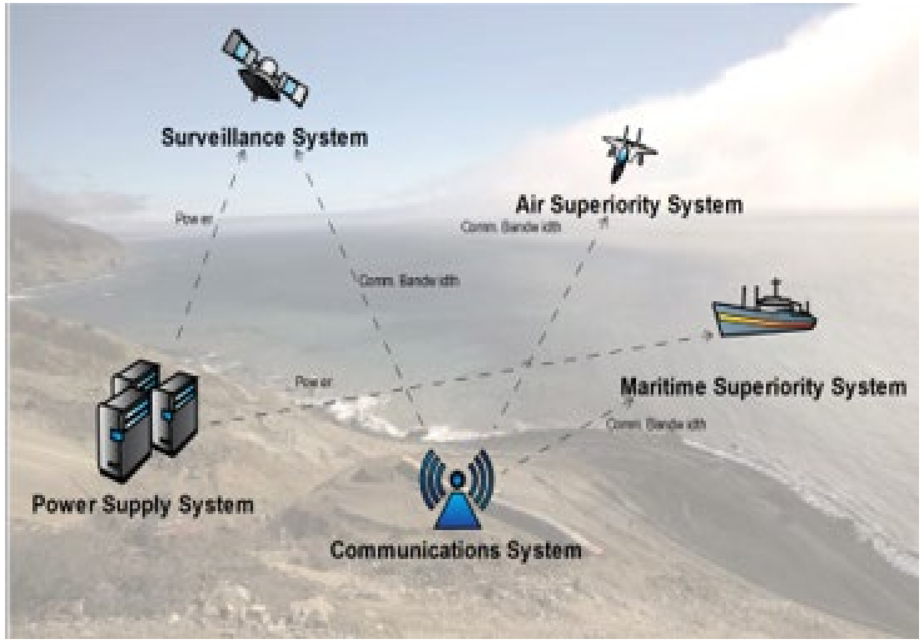
- In our example, each domain i.e., Air Superiority System(s) is accounted as a β-level system with constituent α-level systems.

- Each of the sub-system suppliers, system manager, and SoS managers have **independent goals** of employing data analytics to improve their figures of merit.

- For the SoS capability, right **information** pathways and connecting data sets becomes necessary for SoS-level predictive and prescriptive analytics.



Figure(above): SoS representation Example



AMPHIBIOUS WARFARE SCENARIO

- In this research, we address this problem by first formulating the SoS capability measure based on acquiring multiple systems within the **DoD application domain**. Then demonstrate how the SoS capability evolves due to **sharing** preferences between sub-hierarchical systems while maintaining the independent system objectives.

- A synthetic, multi-objective SoS acquisition problem is based on Amphibious Warfare Scenario which is a multi-domain problem involving air, ground, naval, and space systems, inspired by World War II.

- The systems in Amphibious Warfare interact to provide logistical support and system-level capabilities to achieve certain SoS-level capabilities

- The focus of the study will be on three SoS capabilities related to an amphibious warfare scenario – Air Superiority, Naval Superiority and Reconnaissance. Each SoS capability is computed using a normalized sum of individual system capabilities in their respective domain.

- A Purdue University developed **Decision Support Framework (DSF)** software is used to run simulations.

DECISION SUPPORT FRAMEWORK

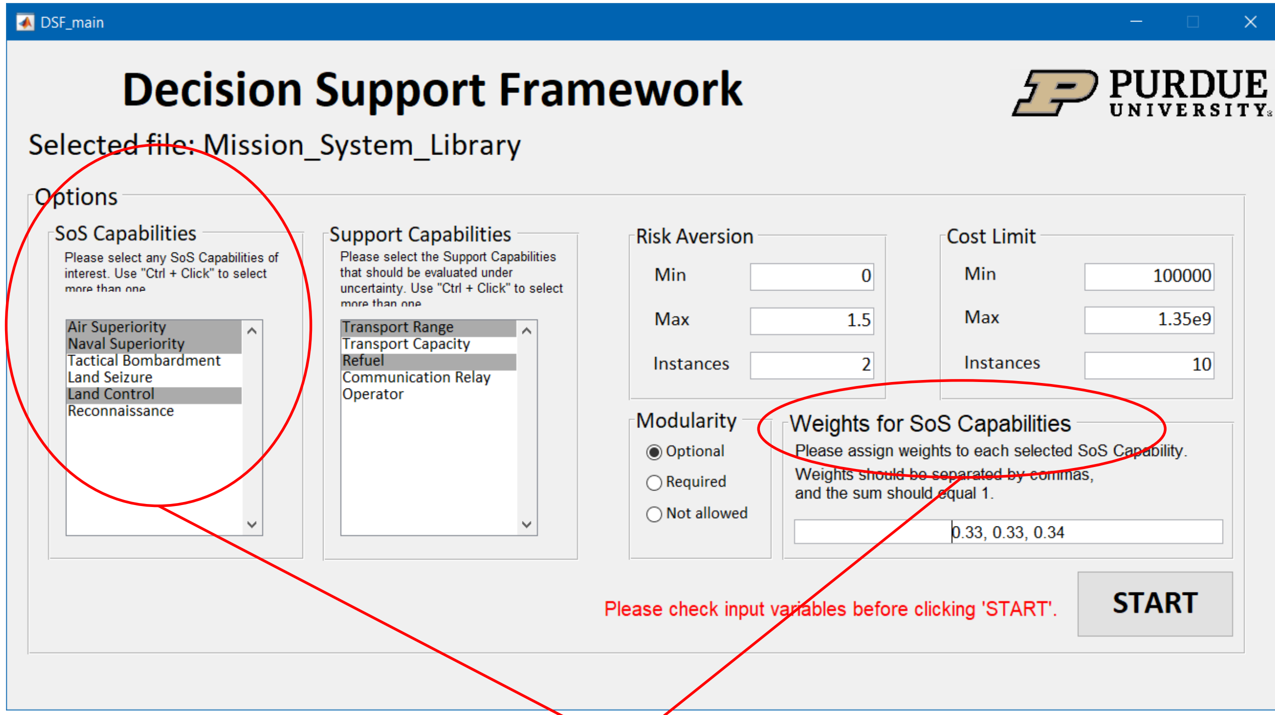
- The primary function of the DSF is to perform quantitative **Analysis of Alternatives (AoA)**. It generates portfolios of systems that provide both the SoS capabilities of interest and the necessary logistical support for the systems.

- This capability is accomplished by integrating **Robust Portfolio Optimization (RPO)** (Davendralingam & DeLaurentis, 2015) analysis tool for SoS which evaluates not only system-level and SoS-level capabilities but also the constraints imposed by interactions between systems.

- The user can create their own **Mission System Library (MSL)** for their specific problem. It is a key means to pass inputs into the DSF

- Implementation of RPO for a certain SoS design problem yields a set of **Pareto optimal portfolios** of cost vs. SoS performance. The DSF runs the RPO tool using as input the system information from the MSL.

- The user can modify the parameters of the analysis in the DSF Main GUI (figure).



- Another feature of the DSF, and the one that is used to investigate our problem statement, is the ability to assign weights to the SoS capability based on the preference for the mission requirement.

MISSION SYSTEMS LIBRARY

Mission_System_Library_AWS_Example

1. Main Sheet: System names, support capabilities (i.e., internal logistic requirement), system capabilities, and capability uncertainties
2. SoS Capabilities: SoS capability names and sets of indices of the system capabilities that contribute to each SoS capability
3. Compatibility Constraints: matrices containing information on compatibility between systems, specification of maximum amount of specific systems allowed in a portfolio
4. Must Have Systems: to indicate any mandatory systems in a portfolio

	A	B	C	D	E	F	G	H
1				Support Input Requirement				
2	No.	System Type	System Name	Transport Range	Transport Capacity	Refuel	Communication Relay	Operator
3	-	-	-	Range (mi)	Capacity (lb)	Fuel capacity (lb)	Rating (n.d.)	Number of Operators
4	1	Air Systems	P-51 Mustang	0	2000	2795	0	1
5	2		B-17 Flying Fortress	0	6000	18500	0	10
6	3		C-47	0	0	5369	0	4
7	4		B-52H Stratofortress	0	60000	321000	1	5
8	5		B-2 Spirit	0	40000	167000	1	2
9	6	Ground Systems	Infantry Platoon	10	1845	0	0	42
10	7		M114 155mm Howitzer	12480	12480	0	0	4
11	8		M-4 Sherman	150	1251	869	0	5
12	9		M8 Greyhound	175	274	353	0	4
13	10		Jeep Willis	0	0	95	0	1
14	11		"Deuce and a half" (supply truck)	0	0	378	0	1
15	12		Advanced Targeting Pod	0	0	0	0	0
16	13		TARDEC Chassis	0	0	378	0	1
17	14		TARDEC Anti Air Module	100	879	0	0	4
18	15		TARDEC Artillery Module	100	1750	0	0	4
19	16		TARDEC Personal Module	100	0	0	0	0
20	17		Bofors 40 mm gun (L60)	100	4800	0	0	4
21	18		Refuel Depot	0	0	0	0	0
22	19		Resupply Depot	0	0	0	0	0
23	20	Naval Systems	Allen M. Sumner Destroyer	0	0	0	0	336
24	21		Higgins Boat (LCVP)	0	0	0	0	3
25	22		Landing Ship, Tank (LST)	0	0	0	0	140
26	23		Battleship	0	0	0	0	2,220
27	24	Space Systems	Ultrahigh Frequency Follow-on (UFO) Communication Satellite	0	0	0	0	100
28	25		Wideband Global Satellite Communication Satellite (WGS)	0	0	0	0	100
	26	Human	General Personnel	0		0	0	0

1 Main Sheet | 2 SoS Capabilities | 3 Compatibility Constraints | 4 "Must Have" Systems | 5 Conditional Must Ha

Systems

Support requirements

3				Robustness (n.d.)	Robustness (n.d.)	Robustness (n.d.)	Robustness (n.d.)									
4	1	Air Systems	P-51 Mustang	0, 0, 0	0, 0, 0	0, 0, 0	0, 0, 0	1650, 360	0, 0	0, 0	2	1	$582,000.00	N	0	0
5	2		B-17 Flying Fortress	0, 0, 0	0, 0, 0	0, 0, 0	0, 0, 0	400, 150	0, 0	0, 0	1	1	$3,399,600.00	N	0	0
6	3		C-47	0, 0, 0	0, 0, 0	0, 0, 0	0, 0, 0	3800, 160	0, 0	0, 0	1	1	$2,173,800.00	N	0	200
7	4		B-52H Stratofortress	0, 0, 0	0, 0, 0	0, 0, 0	0, 0, 0	4400, 525	0, 0	0, 0	2	2	$78,900,000.00	N	0	0
8	5		B-2 Spirit	0, 0, 0	0, 0, 0	0, 0, 0	0, 0, 0	3450, 560	0, 0	0, 0	2	2	$3,423,000.00	N	0	0
9	6	Ground Systems	Infantry Platoon	1, 1, 1	0, 0, 0	0, 0, 0	0, 0, 0	0, 0	10, 3	0, 0	1	0	$8,876.91	N	0	0
10	7		M114 155mm Howitzer	9, 4, 1	0, 0, 0	0, 0, 0	0, 0, 0	0, 0	0, 0	0, 0	1	1	$182,581.95	N	0	0
11	8		M-4 Sherman	2, 3, 3	0, 0, 0	0, 0, 0	0, 0, 0	0, 0	150, 30	0, 0	1	1	$701,849.94	N	0	0
12	9		M8 Greyhound	1, 2, 2	0, 0, 0	0, 0, 0	0, 0, 0	0, 0	175, 55	0, 0	1	1	$359,147.56	N	0	0
13	10		Jeep Willis	0, 0, 0	0, 0, 0	0, 0, 0	0, 0, 0	0, 0	150, 65	0, 0	1	1	$1,575.21	N	0	70
14	11		"Deuce and a half" (supply truck)	0, 0, 0	0, 0, 0	0, 0, 0	0, 0, 0	0, 0	150, 45	0, 0	1	0	$19,879.13	N	0	600
15	12		Advanced Targeting Pod	0, 0, 0	0, 0, 0	0, 0, 0	0, 0, 0	0, 0	0, 0	0, 0	2	2	$1,000.00	Y	0	0
16	13		TARDEC Chassis	0, 0, 0	0, 0, 0	0, 0, 0	0, 0, 0	0, 0	100, 45	0, 0	0	0	$142,404.01	Y	0	200
17	14		TARDEC Anti Air Module	2, 2, 2	0, 0, 0	0, 0, 0	0, 0, 0	0, 0	0, 0	0, 0	1	1	$25,000.00	Y	0	0
18	15		TARDEC Artillery Module	5, 2, 3	0, 0, 0	0, 0, 0	0, 0, 0	0, 0	0, 0	0, 0	1	1	$25,000.00	Y	0	0
19	16		TARDEC Personal Module	0, 0, 0	0, 0, 0	0, 0, 0	0, 0, 0	0, 0	0, 0	0, 0	0	0	$20,000.00	Y	0	100
20	17		Bofors 40 mm gun (L60)	3, 2, 1	0, 0, 0	0, 0, 0	0, 0, 0	0, 0	0, 0	0, 0	0	0	$100,000.00	Y	0	0
21	18		Refuel Depot	0, 0, 0	0, 0, 0	0, 0, 0	0, 0, 0	0, 0	0, 0	0, 0	0	0	$0.00	N	0	0
22	19		Resupply Depot	0, 0, 0	0, 0, 0	0, 0, 0	0, 0, 0	0, 0	0, 0	0, 0	0	0	$0.00	N	0	100
23	20	Naval Systems	Allen M. Sumner Destroyer	0, 0, 0	4, 3, 3	4, 3, 3	4, 4, 4	0, 0	0, 0	3300, 20	2	1	$152,000,000.00	N	0	0
24	21		Higgins Boat (LCVP)	0, 0, 0	1, 1, 2	1, 1, 2	1, 1, 2	0, 0	0, 0	10, 9	0	1	$229,300.00	N	0	200
25	22		Landing Ship, Tank (LST)	0, 0, 0	4, 3, 3	4, 3, 3	4, 3, 3	0, 0	0, 0	10000, 12	2	1	$36,320,100.00	N	0	1000
26	23		Battleship	0, 0, 0	9, 3, 3	9, 3, 4	9, 4, 3	0, 0	0, 0	5900, 21	2	1	$100,238,000.00	N	0	0
27	24	Space Systems	Ultrahigh Frequency Follow-on (UFO) Communication Satellite	0, 0, 0	0, 0, 0	0, 0, 0	0, 0, 0	0, 0	0, 0	0, 0	2	2	$382,000,000.00	N	0	0
28	25		Wideband Global Satellite Communication Satellite (WGS)	0, 0, 0	0, 0, 0	0, 0, 0	0, 0, 0	0, 0	0, 0	0, 0	2	2	$300,000,000.00	N	0	0
	26	Human	General Personnel	0, 0, 0	0, 0, 0	0, 0, 0	0, 0, 0	0, 0	0, 0	0, 0	0	0	$170.00	N	0	0

System capabilities

Cost

Modular properties

Uncertainty

SIMULATION SETUP

- Common occurrence: differences in interpretation of the **mission requirements** either due to lack of communication or judgement.
- This study investigates how such **dissimilarities** in the definition of the mission requirements of one contributing individual from another affects the final SoS performance and cost.
- This then leads to the issue of conflicting objectives among the team of acquisition managers or SoS designers.
- We run 30 cases of varying weights among the team of acquisition managers to understand the **variance in portfolios, performance and cost** of the SoS.
- Each of these cases represent an instance of the previously discussed uncertainty in definition of the mission requirement by stakeholders (varying weights in air superiority, naval superiority, and reconnaissance).
- Figure shows the weight distribution for each of the SoS capabilities in the 30 unique cases.

	Weights		
Cases	AS	NS	Recon
1	0.8	0.1	0.1
2	0.7	0.2	0.1
3	0.7	0.1	0.2
4	0.6	0.2	0.2
5	0.6	0.3	0.1
6	0.6	0.1	0.3
7	0.5	0.1	0.4
8	0.5	0.2	0.3
9	0.5	0.3	0.2
10	0.5	0.4	0.1
11	0.4	0.5	0.1
12	0.4	0.4	0.2
13	0.4	0.3	0.3
14	0.4	0.2	0.4
15	0.4	0.1	0.5
16	0.3	0.6	0.1
17	0.3	0.5	0.2
18	0.3	0.4	0.3
19	0.3	0.3	0.4
20	0.3	0.2	0.5
21	0.3	0.1	0.6
22	0.2	0.7	0.1
23	0.2	0.6	0.2
24	0.2	0.5	0.3
25	0.2	0.4	0.4
26	0.2	0.3	0.5
27	0.2	0.2	0.6
28	0.2	0.1	0.7
29	0.1	0.1	0.8
30	0.1	0.8	0.1

Figure: 30 simulation test cases

RESULTS

PORTFOLIOS

- For each case, the DSF produces portfolios containing data about the various possible portfolios and its associated SoS performance index and cost.
- A portfolio is a feasible combination of systems, which includes some that provide the required capabilities and others that provide the needed support.
- Figure is an example (case 1) for a portfolio generated for a test case. Each column is a Pareto-optimal portfolio for a given budget limit.
- *Zeros* mean that the corresponding architecture does not utilize the system in question. *Ones* indicate systems that are part of the architecture.
- This data will give the user insight on how these suggested architectures differ amongst themselves and how they compare with other cases.

In this example result(figure), it is observable that when the architectures switch to a combination that includes one or more different systems, better performing yet expensive, the SoS capability improves. This possibility of various permutations of system architectures make a portfolio-based study more relevant and accurate for SoS acquisition problems.

SoS capability	0	0.0624	0.0691	0.0737	0.0737
Cost	$0.00	$ 145.24M	$ 297.24M	$ 597.24M	$ 679.24M
P-51 Mustang	0	1	1	1	1
B-17 Flying Fortress	0	1	1	1	1
C-47	0	0	0	0	0
B-52H Stratofortress	0	0	0	0	0
B-2 Spirit	0	0	0	0	0
Infantry Platoon	0	1	1	1	1
M114 155mm Howitzer	0	0	0	0	0
M-4 Sherman	0	1	1	1	1
M8 Greyhound	0	1	1	1	1
Jeep Willis	0	1	1	1	1
"Deuce and a half" (supply truck)	0	0	0	0	0
Advanced Targeting Pod	0	1	1	1	1
TARDEC Chassis	0	0	0	0	0
TARDEC Anti Air Module	0	0	0	0	0
TARDEC Artillery Module	0	0	0	0	0
TARDEC Personal Module	0	0	0	0	0
Bofors 40 mm gun (L60)	0	0	0	0	0
Refuel Depot	0	1	1	1	1
Resupply Depot	0	0	0	0	0
Allen M. Sumner Destroyer	0	0	1	1	1
Higgins Boat (LCVP)	0	1	1	1	1
Landing Ship, Tank (LST)	0	1	1	1	1
Battleship	0	1	1	1	1
Ultrahigh Frequency Follow-on (UFO) Communication Satellite	0	0	0	0	1
Wideband Global Satellite Communication Satellite (WGS)	0	0	0	1	0
General Personnel	0	1	1	1	1

PARETO FRONTIERS

- Portfolio Performance Frontiers where the SoS Performance Index is mapped with its corresponding costs is plotted.
- Each of these portfolio performance frontiers identify the best possible solution (architecture) for a given cost.
- Every distinguishable point on the frontier is a feasible architecture. With increase in budget, as expected, better performing systems are acquired to form the SoS architecture.
- This results in better performing SoS architectures within the same scenario.
- Closely inspecting and comparing the two pareto frontiers it is evident that while the shape/form of the two is similar, the data points are not the same.
- This indicates that different weight preferences for the SoS capability produce portfolios that provide different performances.

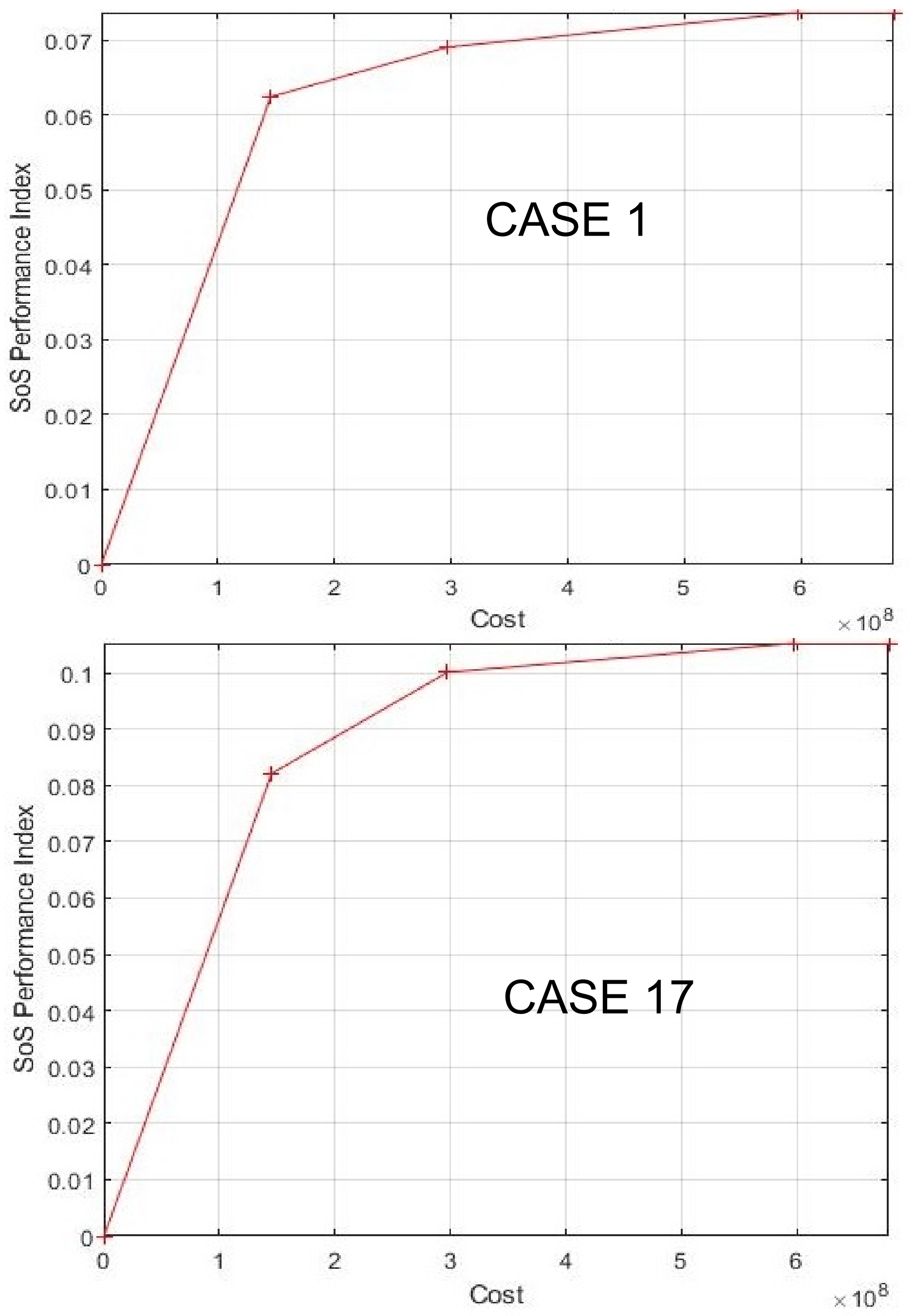
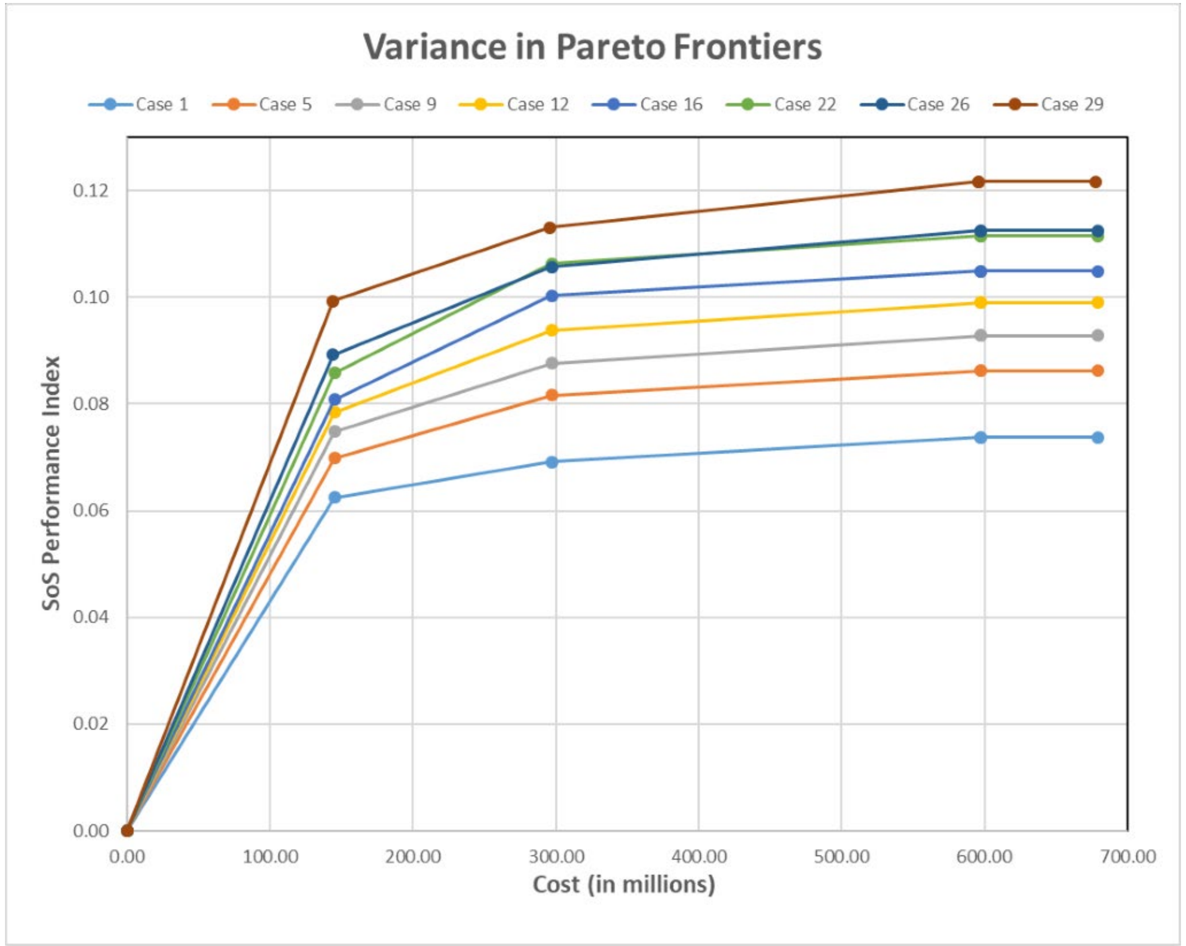


Figure: Performance Pareto Frontiers

VARIANCE IN FRONTIERS

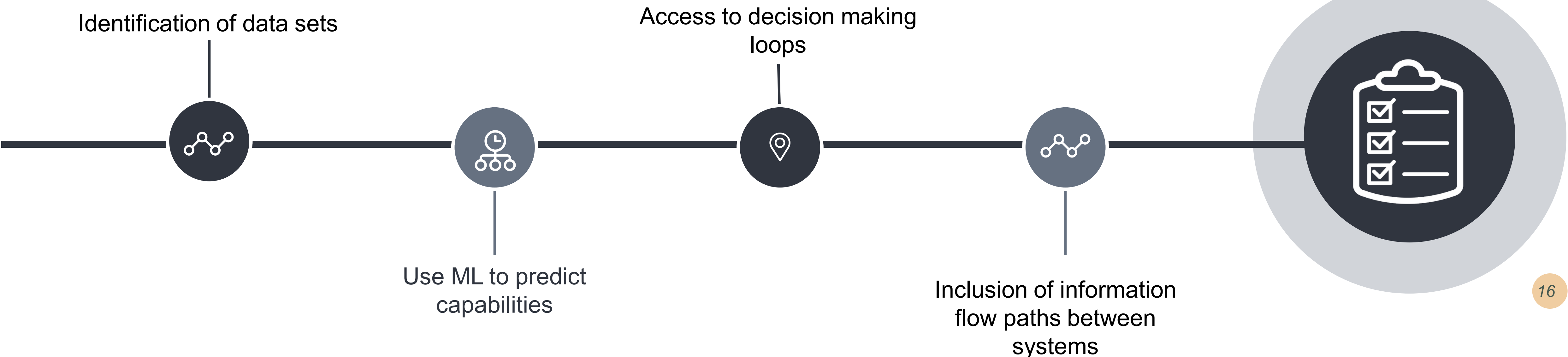
- Case 1 had a weight of 0.8 (out of 1) and Case 29 had 0.1 for Air Superiority and as stated the SoS performance index for their respective portfolios are inversely related to the value of the assigned weights.
- Leading to two portfolios with a sizeable difference in their performance index. Another influencing factor in any acquisition problem is the restrictive nature of the proposed budget i.e., cost.
- By using RPO, the accountability of cost-based comparisons are visible too.
- Instances where the performance index of a portfolio for one case (case 26) is higher than the other (case 22) for a specified cost value. However, with an increase in cost to a higher value, the previous trend does not hold true.



TAKEAWAYS & FUTURE WORK

- *DSF shows that when the portfolios switch to a combination that includes one or more different systems, better performing yet expensive, the SoS capability improves. This highlights the importance of sharing preferences and connecting data sets across SoS.*
- *Any uncertainty in SoS requirement definition or system capabilities has a direct effect on the resulting performance. These differences thus reflect various information and decision by stakeholders and will be used in future steps*
- *Instances where the performance index of a portfolio for one case is higher than the other for a specified cost value but contradictory results exist too. This shows that final performance is more than just system capabilities and SoS capabilities but also include the contribution by the interaction of various systems.*

- A major challenge that we aim to address in future is identification of which datasets needs to be connected across the SoS, since a fully connected Big Data enterprise is unlikely to be pragmatic in the real world. Further our focus is on investigating machine learning techniques that can predict the SoS capability based on having access to decision making loops at the system level and prescribe a path forward for generating information flows between systems in the SoS.



THANK YOU!

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