Reducing the Costs of Engineering Design Changes Through Adoption of a Decision Support and Knowledge Management System Early in the Design

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Abstract— *In complex design projects, engineering and program management disciplines often work in isolation leading to inconsistencies in product information, tracking of design changes, challenges in decision-making, and potential product and project failure. Moreover, the lack of information early in the design can postpone decision-making further into the design cycle when it becomes more expensive and difficult to make changes. Differences across disciplines in their respective practices and lack of a common platform for exchanging information have contributed to this gap. In bridging this gap, an analytical decision support system is presented that enhances engineering design change management and knowledge management early in the design. The human factors involved in embracing such a system and adopting a structured knowledge management framework are investigated through a review of knowledge management theory, conducting a social network analysis, and analyzing the results of a survey of a west coast shipyard design team. To understand enablers and barriers to design change management and knowledge management, a system dynamics causal loop diagram is presented. The decision support system and design change - knowledge management framework presented in the current study is a viable option to bring multiple disciplines together on a common platform and to provide a method to enable informed decisions early in the design cycle. The iterative and dynamic nature of this model is aligned with the principles of agile management as well as other best practices in managing programs and complex systems.*

Keywords—*systems engineering, program management, multi-criteria, multi-discipline, multi-attribute, tradespace exploration, marine integrated power system, decision-making, social network analysis, knowledge management, system dynamics*

I. Introduction

Systems engineering and program management can often work in isolation within a complex project environment where challenges with information flow early in the design can lead to cost overruns and schedule delays.

Bridging solutions provide for coupling of information between systems engineering and project management through the notion of aggregate common indicators and sharing of this information through dashboards [1]. These bridging solutions include Multi-Disciplinary System Design Optimization (MSDO); combining models from each discipline while recognizing common design variables, optimization of objectives, and adherence to constraints.

The need for analytical decision management tools is supported by project and product failures in the past where it has been difficult to decide what to change in product design development when everything seems to have an influence [2].

Implementing a MSDO model and Decision Support System (DSS) involves organizational and social network complexities that can impede their success. Knowledge management can enhance the ability to make informed decisions for design changes early in the design. Postponing design changes can lead to increased costs when it is more expensive and difficult to implement change.

The focus in the current study is to present a MSDO model based on product normalized technical and quality measures, to provide visualization of deviations and trends in design attributes for product design development and decision-making, and to demonstrate how knowledge may be brought forward early in the design by using MDSO and a DSS.

II. Background and Theory

In developing a generic MDSO and DSS, several models were integrated in the current study to form a Multi-Criteria Decision-Making - Integrated Analytical Framework (MCDM-IAF) for enhanced decision making, design change management, and knowledge management early in the design cycle.

The systems engineering models considered in the current study include Multi-Attribute Tradespace Exploration (MATE) and Design Structure Matrices (DSM); the program management models include the Standard Risk Model (SRM) and Decision Payoff models. Six sigma methodology and process control measures are included in the MCDM-IAF for visualization of patterns and trends in system attributes, as affected by design changes.

In systems engineering, MATE may be defined as quantitatively exploring the relationships within a multivariable design space to identify feasible alternatives that satisfy system objectives and attributes, typically in support of

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designing, selecting, or optimizing a system. It is a decision-making framework that applies decision theory to model-based design [3]. The MATE model, and its inherent system physical laws, forms the first component in the MCDM-IAF. The multi-attribute utility functions (U) developed in the current study represent the weighted sum of several performance, survivability, and program attributes.

$$U = \sum_{i=1}^{n} k_i u_i \tag{1}$$

As design changes can affect several components within a system, the level of changeability and change propagation is of value in understanding the consequences of change. The DSM for indicating changeability of components forms the second component in the MCDM-IAF.

The SRM component change likelihood (Li) values form the DSM diagonal, while likelihood values of change propagation from one component to another are assigned to the DSM off-diagonals. Calculating the impact of component redesign follows similar logic with a distinct DSM impact table. Using component change propagation trees, direct and indirect change effects by way of indices are determined for components [4,5]. For instance, the Incoming Change Likelihood (ICL) index describes how likely a component is expected to be changed due to change propagation. The Incoming Change Impact (ICI) index describes the impact of component redesign. The Outgoing Change Risk (OCR) describes how a component can affect other system components in terms of change propagation.

$$ICL = \frac{\Sigma\, Likelihood\ Row\ Entries}{Total\ Number\ of\ Components} \tag{2}$$

$$ICI = \frac{\Sigma\, Impact\ Row\ Entries}{Total\ Number\ of\ Components} \tag{3}$$

$$OCR = \frac{\Sigma\, Risk\ Column\ Entries}{Total\ Number\ of\ Components - 1} \tag{4}$$

These indices may be normalized to provide a relative indication of components least and most likely affected by changes in a system. Components with a high OCR value have a strong influence on other components and therefore should be made less likely to change where the design principles of modularity and loose coupling may be appropriate. Conversely, systems with a low OCR are less likely to change and therefore may be well suited for standardization [4].

For design changes proposed early in the design, represented as likely changes within the SRM, the visualization of their impact on performance, survivability and cost attributes may be achieved through six sigma and process capability measures. It's proposed in the current study that the tracking of design attributes may be viewed as analogous to tracking process behavior. Process Capability (Cp) is a common six-sigma measure used to compare a process' natural variability against engineering tolerances and provides a measure of variability fit within tolerances [6, 7].

$$C_p = \frac{USL - LSL}{6\sigma} \tag{5}$$

The Cp measure can monitor the variability in attribute values over time, within the non-dimensional Upper Specification Limit (USL) value of one and the Lower Specification Limit (LSL) value of zero. The higher the Cp value; the better, as it represents the number of times the process fits within limits.

Cpk is a measure of the position of the process, attributes in the current study, in relation to the tolerance or specification limits. Should Cpk be below one, the process will infringe upon specification limits. The lower of the two Cpk values is typically used for process capability. Of interest in the current study, Cpk may represent a level of robustness in design.

$$C_{pk} = min\left(\left(\frac{USL - avg}{3\sigma}\right), \left(\frac{avg - LSL}{3\sigma}\right)\right) \tag{6}$$

Both Cp and Cpk values are utilized within the MCDM-IAF in providing a measure of variability and capability in attribute levels. In applying these measures, low Cp and Cpk values will point toward design attributes that require investigation and may also serve as a trigger to decide whether or not to re-baseline or freeze portions of the design.

Traditional process control measures have been applied to long production runs, requiring 15 to 25 data points to accurately reflect process performance [7]. In the current study, a high number of design change scenarios provide for enough data points to reflect attribute performance.

Decisions made early in the design cycle can have the greatest impact while at the same time; there is little product information and high uncertainty [8]. Costs and time could be saved if it were possible to make quick, yet accurate, assessments about the impact of a change prior to implementing change [9].

Early knowledge can include typical design change scenarios that are played out where risk levels, changeability of components, costs, and schedule are investigated with strategies developed to ensure system attributes remain within design limits.

The availability of data and information early in design can move the Knowledge curve in Figure 1 to the left where design changes can be more easily implemented.

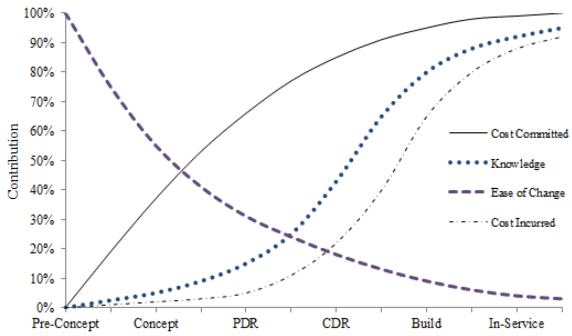

Fig. 1 Knowledge, Changeability and Costs in Design

It is proposed in the current study that the Knowledge curve can be moved to the left by bringing together multi-dimensional information through use of the MCDM-IAF and DSS. Additionally, the Ease-of-Change curve can be moved

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up by applying appropriate design principles and leveraging the DSM for system component changeability.

The knowledge economy operates on the complexities of human connections that affect the flow of information and knowledge [10]. Patterns in the network connections can provide insight into how successful teams are performing. These networks can be analyzed through surveys and Social Network Analysis (SNA) software such as Inflow®.

In the current study, a shipyard design team is analyzed using SNA and the measures of Density, Power and the Characteristic Path Length (CPL). The analysis is conducted for two typical design change scenarios.

The measure of network Density may be defined as the proportion of network ties or links to all potential ties. The measure of Power is related to organizational structure; in a hierarchical structure the leader would have ultimate Power at a value of one. With a more horizontal interconnected structure, increased collaboration and relationships distribute Power more evenly. The Characteristic Path Length (CPL) of a network is the shortest path length between two nodes averaged over all pairs of nodes. The shorter the path; the more easily information can flow.

The learning process can be linked to the social network, culture, values and willingness of an organization to learn. In ship design, knowledge possessed by engineers may be viewed as the main resource leading to competitive advantage [11]. On the other hand, the knowledge possessed by other key stakeholders within the value chain may be equally important. This knowledge may take the form of explicit or tacit knowledge. Explicit knowledge may include drawings, technical specifications, and plans; tacit knowledge may include experience, expertise and the aspects of learning.

From a literature review, it is not apparent that quantitative measures exist for knowledge generation and transfer. In the current study, knowledge generation may be measured by the number of design change scenarios played out and strategies developed, lessons-learned, and typical changes found in similar system design projects.

Knowledge economy theory considers the life cycle of knowledge as a commodity, when to develop professional knowledge, and how to combine sources of knowledge [12]. Knowledge economy theory addresses the production and distribution of knowledge. In the current study, the flow of knowledge may analyzed through SNA and described through a system dynamics Causal Loop Diagram (CLD).

System dynamics is used to analyze the behaviour in organizational or social systems over time through describing and evaluating causal relationships. It can provide for a better understanding of complex systems and their behaviour [13]. System dynamic loops can describe how knowledge generation and transfer can be impeded or enhanced.

The feedback processes in the dynamic model can include design iterations and design changes [14]. By analyzing the system dynamics model, policies and processes may be revised to move knowledge forward in design cycle and improve design change management.

It is proposed that aspects of game theory, along with the MCDM-IAF model and visualization component, can help manage collaborative decision-making.

Game theory originates from games such as chess where they are mathematically expressed and where players must think ahead and devise strategies. In game theory, the game is described by team (Tn), strategies, and possible payoffs for the players, as depicted in Figure 2. Using game theory for decision-making can be useful in managing multi-discipline collaborative design and design changes. Compared with other multi-objective optimization methods, game theory methods have been shown to converge faster with better robustness [15].

With insight into the impact of design changes, a decision can be made using both monetary and system attribute payoff tables. This can enhance informed decision-making in assessing proposed design changes early in the design process. The different project teams can develop strategies for deciding what design changes to implement based on payoff tables and what-if scenarios. However, human and social capital can affect what team has the greatest influence on these decisions.

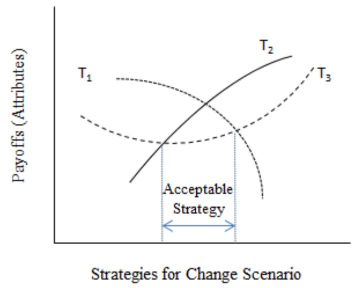

Fig. 2 Payoffs and Strategies for a Change Scenario

In game theory, the players may adopt a non-cooperative model based on a Nash equilibrium or a cooperative model based on a pareto optimal solution [15]. In the current study, it is assumed the cooperative model is adopted and that players are willing to compromise to improve the overall payoffs. On the other hand, non-cooperation may reflect reality in the ship design high stress environment.

III. Results and Discussion

The elements of the proposed MCDM-IAF in the current study are depicted in Figure 3.

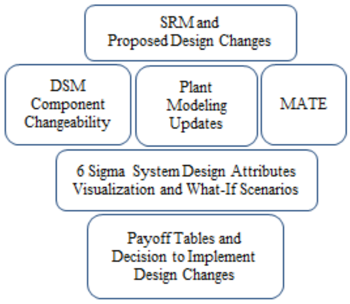

Fig. 3 MCDM-IAF Components

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The MCDM-IAF process for design changes includes the review of the MATE model and six sigma visualization charts for the variability in system attributes. The mapping of change event probabilities from the SRM to primary components within the DSM provides for an innovative approach in determining changeability of design components.

With the change event probability and total potential loss calculated within the SRM, a decision can be made using payoff tables, as supported by Bayes' decision theory. The MCDM-IAF process includes consideration to both monetary as well as design attribute payoff tables.

In validating functionality of the MCDM-IAF, a case study was used that involves the design of a notional marine Integrated Power System (IPS). The selected IPS concept design consists of two conventional diesel generators, two conventional gas turbines, an advanced control system, a 320 MW Ultra-Capacitor set, Zonal Electrical Distribution (ZED), and a machinery raft configuration.

The typical risks leading to IPS design changes were obtained through interviews with two shipyards, interviews with an electrical hydro company and electrical plant manufacturer, as well from a literature review [16,17].

The top ten risks were used as input into the SRM with estimated probabilities for risk events and program impact; the risk and total loss at the technical system level were calculated through the DSM and MATE model.

From the SRM register, one of the highest risks was a change to regulatory requirements, For the case study, this led to a proposed change in the type of Diesel Generator (DG) set, identified as risk R4. It was assumed the new regulation would force redesign of the DG system to accommodate IMO Tier III emission requirements. This is an example of obtaining uncertain information early in the design where working toward more informed decisions can reduce costs.

The R4 risk and proposed change was played out within the MCDM-IAF to demonstrate functionality of the prototype framework and interactive DSS. To determine how the system component risk influenced change propagation, the DSM methodology was followed. With the use of change propagation trees, DSM tables were developed for component likelihood of change, impact and risk. The combined component probability for risk is shown in Table 1.

Table 1. IPS DSM Likelihood of Component Design Change

Risk with Influence of Likelihood and Impact on Component		DG	PMS - MPC	GT	HESS - UC	ZED	Raft
Element Name		a	c	b	d	e	f
DG	a		0.01			0.01	0.00
PMS - MPC	c	0.14		0.04	0.11	0.02	
GT	b		0.01			0.01	0.00
HESS - UC	d		0.01				
ZED	e	0.06	0.00	0.02			
Raft	f	0.05		0.01			

The component ICL, ICI and OCR values were calculated from respective DSM likelihood, impact, and risk tables.

To show the relative level of changeability in IPS components, the ICL, ICI and OCR values were normalized and ranked, as shown in Table 2.

Table 2 IPS DSM Normalized OCR for a Component

Element Name		ICL	ICL Normalized	ICI	ICI Normalized	OCR Risk	OCR Risk Normalized
DG	a	0.15	**0.50**	0.15	**0.47**	0.05	**1.00**
PMS - MPC	c	0.23	**1.00**	0.22	**1.00**	0.00	**0.07**
GT	b	0.08	**0.00**	0.13	**0.35**	0.01	**0.26**
HESS - UC	d	0.09	**0.06**	0.08	**0.00**	0.02	**0.44**
ZED	e	0.12	**0.28**	0.14	**0.40**	0.01	**0.18**
Raft	f	0.12	**0.26**	0.10	**0.15**	0.00	**0.00**

The change to the DG system is viewed as significant, in that, it will likely require reconfiguration of the IPS where several design variables and attributes will be affected. Again, the change in attributes may be assessed through the proposed MCDM-IAF.

The normalized ICL and ICI values for components are depicted in Figure 4. The DG and Power Management System-Model Predictive Control (PMS-MPC) are most susceptible to change based on event and component impact probabilities, as estimated within the SRM and DSM.

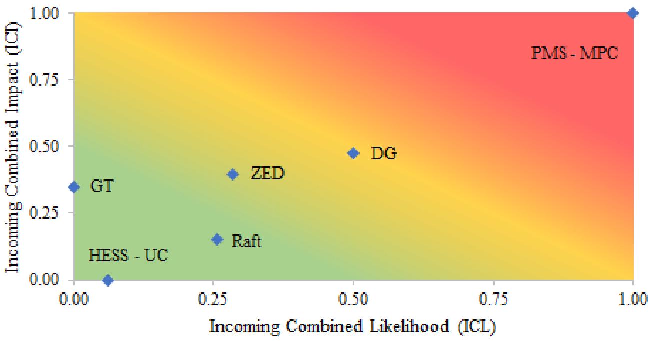

Fig. 4 IPS Changeability of Components

As component types, design variables, risk, and impact values are changed, there can be a corresponding change to system component changeability values. This information can be important in deciding where and when design principles and component changes may be necessary. Should components be made more modular, then DSM impact probabilities would have to be updated as part of an iterative approach. The interactive component of the MCDM-IAF and DSS provides a dynamic chart to visualize component changeability.

From the MATE model, the total potential redesign engineering costs for the affected DG component provides an input into the SRM. Both engineering and program costs are used as inputs into the Bayes' decision payoff tables. The change in attribute levels from a potential design change are viewed as additional payoff tables.

As depicted in Figures 5 and 6, the proposed MCDM-IAF visualization component includes interactive controls for adjusting design variables, component types, risks, and impact of redesign, thereby allowing for visualization of the impact on design and program attributes.

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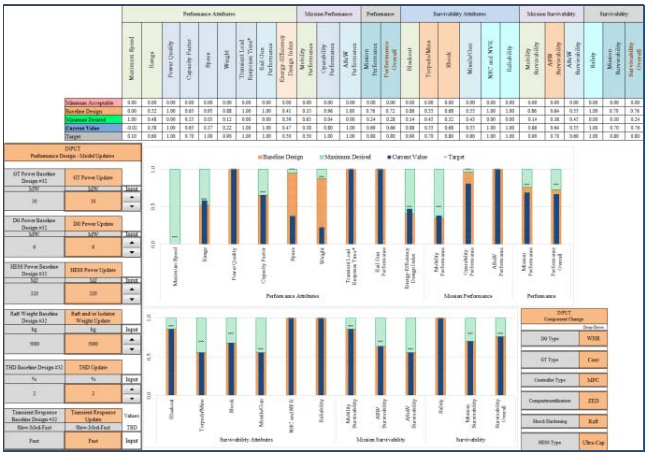

Fig. 5 MCDM-IAF Interactive Visualization Tool for Changes to Design Variable Values and Component Types

Risk ID	IPS Risk Event	Primary IPS Component Affected	Risk Event Probability (input into DSM) %	Design Rework Impact Probability (input into DSM) %	Program Impact Probability %	Program Risk Likelihood %	Constant Expected Loss Le Threshold ($K)	Input
R1	Supplier not able to keep up with demand, delivery date 2 months beyond estimated	DG	75	50	30	23	20	
R2	Increased Speed Requirement	GT	25	50	20	5		
R3	VFI Understated Power	GT	25	40	20	5		
R4	Tier II to III Emission Requirements	DG	75	50	20	15		
R5	Lower than expected TRL	HESS-UC	50	30	10	5		
R6	System Component Conflict	Raft	20	40	20	4		
R7	Increased harmonics	ZED	30	30	10	3		
R8	Component physical size too large	DG	75	50	20	15		
R9	Control system designed too early	PMS-MPC	10	40	30	3		
R10	Increased fuel prices	DG	75	50	10	8		

Fig. 6 MCDM-IAF Interactive Visualization Tool for Changes to Risk and Redesign Impact Levels

The change in attribute levels can be visualized in Figure 5; the patterns and trends in these attributes can be visualized in Figure 7, including an indication of a change in variability and capability within assigned tolerances.

The visualization of patterns and trends in these attributes are conducive to the natural way people can learn and retain knowledge. The non-dimensional normalized values for these attributes provide for a common language among multiple disciplines.

The values of Cp, process variability, and CpK, process capability, for design attributes are calculated in the background and are represented as being within or outside of tolerance. For the IPS case study, the R4 DG change risk is played out within the MCDM-IAF model where resulting Cp and CpK values for the attributes of Speed, physical Space, Costs, and Schedule Slippage are negatively affected.

These set-based attributes include lower and upper thresholds that relate back to the MATE model and system mandatory requirements. Based on feedback from the MCDM-IAF visualization tool, strategies can be explored by the project teams to find solutions in bringing attribute levels within tolerance and toward goal-based values.

These strategies could involve the supply chain team seeking out vendors with higher power-to-weight or power-to-space ratios for prime movers. It could involve engineering teams seeking out new ways to increase speed.

The use of set-based goal-based attributes, concurrent engineering, and collaborative gaming of scenarios can provide flexibility in sourcing feasible system components early in the design; this requires strategies aimed at positioning attributes somewhat higher than minimal thresholds for robust design. Conversely, relaxing attribute constraints may result in an improved design at the expense of deficient attributes, where overall ship-level aggregated attributes may have to be negotiated with other system owners.

Capability	IPS Attribute/Month	Variability Within Tolerance	Capability Within Tolerance	Trend
Performance Attributes	Maximum Speed	Yes	No	
	Range	Yes	Yes	
	Power Quality	Yes	Yes	
	Capacity Factor	Yes	Yes	
	Space	Yes	No	
	Weight	Yes	Yes	
	Transient Load Response Time*	Yes	Yes	
	Rail Gun Performance	Yes	Yes	
	Energy-Efficiency Design Index	Yes	Yes	
Mission Performance	Mobility Performance	Yes	Yes	
	Operability Performance	Yes	Yes	
	ASuW Performance	Yes	Yes	
Performance	Mission Performance	Yes	Yes	
	Performance Overall	Yes	Yes	
Survivability Attributes	Blackout	Yes	Yes	
	Torpedo/Mine	Yes	Yes	
	Shock	Yes	Yes	
	Missile/Gun	Yes	Yes	
	NSC and NVR	Yes	Yes	
	Reliability	Yes	Yes	
Mission Survivability	Mobility Survivability	Yes	Yes	
	ASW Survivability	Yes	Yes	
	ASuW Survivability	Yes	Yes	
Survivability	Safety	Yes	Yes	
	Mission Survivability	Yes	Yes	
	Survivability Overall	Yes	Yes	
Program	TRL Index	Yes	Yes	
	SRL Index	Yes	Yes	
	Costs ($M)	Yes	No	
	Schedule Slippage	No	No	

Fig. 7 Design and Program Attribute Patterns and Trends

The monetary payoff in Table 3 shows that for R4, alternative 2 in changing the DG to incorporate WHR provides the highest cost payoff for the given event probability. While this traditional Bayes' decision methodology points toward this alternative, the current study proposes that attribute payoff tables also be considered, as shown in Table 4.

Of interest, while alternative 2 results in a higher cost and performance payoff, the Technology Readiness Level (TRL) negatively affects Relative Schedule Slippage (RSS).

Table 3 Bayes' Cost Payoff Decision for Risk R4

Potential New Environmental Regulatory Requirement		Costs Payoff	
Alternatives		New Reg Will Not be Enforced	New Reg Will be Enforced
1	Continue with Current Tier II DG	$200,000	-$100,000
2	Acquire WHR DG to meet Reg Tier III	$250,000	$250,000
	Prior Probability	0.25	0.75
Expected Payoffs			
1	0.25($200,000)+0.75*(-$100,000)		-$25,000
2	0.25($250,000)+0.75*($250,000)		$250,000

Table 4 Attribute Level Payoff Decision for Risk R4

Alternatives		Performance Utility Payoff	Survivability Utility Payoff	TRL RSS
1	Continue with Current Tier II DG	0.73	0.87	78%
2	Change to DG with WHR to Meet Tier III	0.74	0.87	128%

In order to understand how team relationships, strategies and payoffs interact, the matrix in Figure 8 may be used to provide context without the need for calculations.

$$\begin{bmatrix} S_{11} & S_{12} & S_{13} & \cdots & S_{1m} \\ S_{21} & S_{22} & S_{23} & \cdots & S_{2m} \\ S_{31} & S_{32} & S_{33} & \cdots & S_{3m} \\ S_{41} & S_{42} & S_{43} & \cdots & S_{4m} \\ S_{51} & S_{52} & S_{53} & \cdots & S_{5m} \\ S_{61} & S_{62} & S_{63} & \cdots & S_{6m} \end{bmatrix} \left\{ \begin{bmatrix} T_1 \\ T_2 \\ T_3 \\ T_4 \\ T_5 \\ T_6 \end{bmatrix} \right\} = \left\{ \begin{bmatrix} P_1 \\ P_2 \\ P_3 \\ P_4 \\ P_5 \\ P_6 \end{bmatrix} \right\}$$

Fig. 8 Team Strategies and the Game Payoff Matrix

In this matrix, the vector of payoffs (P1, P2,.., Pm)T each represent a list of possible attribute levels, as described within the MCDM-IAF. The strategies (Sn) are played out by the individual teams (Tn) for a particular change scenario. Depending on how collaborative the teams are, a set of strategies may be developed that meet required levels in the list of attributes. Strategies can be selected that help attributes converge to goal-based levels.

The contribution of each team may be at different levels of importance for each change scenario where the strategy of less important teams may be given a lower weighting or be removed . The importance of each team in a scenario may be determined in accordance with the organization's change process rules; this can be validated through SNA.

The aim of gaming design change scenarios in the current study is to promote team collaboration early in the design, establish rule sets for certain scenarios, prevent group think, and to generate tacit knowledge. At the technical level, gaming can help determine a strategy that will maintain attribute levels within tolerance for a given change scenario. Strategies may also be developed early in the designs that are aimed at working toward robust design, with the desire to have attribute levels higher than the lower tolerance level of zero for flexibility in design. Similarly, engineering principles can be applied to key components to reduce the negative impact of design changes, also making for a more robust design.

To obtain SNA data, two scenarios were solicited to a west coast shipyard design team. The first scenario involves changing a DG set to one with waste heat recovery due to imposed more stringent environmental regulations, this was risk R4. The second scenario concerns an error in Vendor Furnished Information (VFI) that requires an increase in the power rating of the Gas Turbines (GT).

The shipyard design project team consists of six sub-teams that form the organization's value chain; Table 5 provides the team composition. From the SNA, individual team Power measures were calculated. These measures are proposed as weightings for teams in the game strategy-payoff matrix. This may provide insight into the level of importance placed on teams for a design change scenario. On the other hand, a more evenly distributed level of power across teams may be imposed through change process rules. Table 6 provides a summary of SNA high-level measures for the two change scenarios.

Table 5 West Coast Shipyard Design Team Composition and SNA Power for Two Change Scenarios

Team	Description	Power Scenario 1	Power Scenario 2
T1	Program Management	0.34	0.60
T2	Electrical Engineering	0.32	0.36
T3	Mechanical and Propulsion	0.31	0.36
T4	Supply Chain	0.80	0.36
T5	Planning and Scheduling	0.36	0.60
T6	Production	0.36	0.36

Table 6 SNA High-Level Measures for Two Change Scenarios

Scenario	Network Density	Standard Deviation of Team Power	Characteristic Path Length
1	60%	0.19	1.4
2	73%	0.13	1.3

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From these results, information flow appears to be more restricted for the first scenario as compared to the second scenario. The network for the first scenario is depicted in Figure 9.

In the first scenario, the network pattern is one where teams are well connected on both sides of team T4 (Supply Chain); however, T4 is viewed as a bottleneck to the flow of information within the network. There appears to be strong communication in pairs for the engineering teams, program management and the supply team, and production and planning teams.

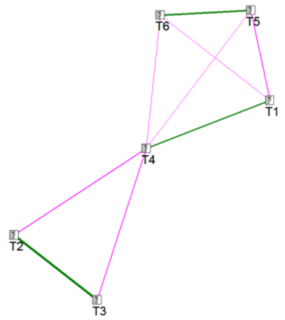

Fig. 9 Social Network for the First Change Scenario

The network for the second scenario is depicted in Figure 10. For this scenario, which involves incorrect VFI, there appears to be increased connectivity of the teams. This may reflect the view of all teams on the importance of VFI flow throughout the network and organization's value chain.

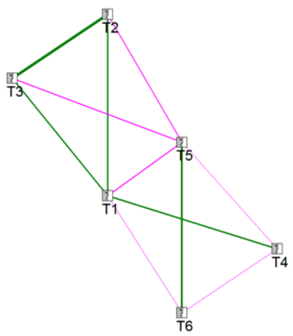

Fig. 10 Social Network for the Second Change Scenario

The west coast shipyard design team responded to a questionnaire asking how knowledge could be increased early in the design. Their answers highlighted the need for a defined change process that includes all factors affecting the final decision and the need for well understood VFI. Through interviews with an east coast shipyard design team, low VFI maturity and late design changes were noted as concerns; their estimated values for the design and build of a marine IPS are depicted in Figure 11.

In the west coast shipyard questionnaire, they were asked about information flow and if there was a need for insight into high-level system attributes, as impacted by design changes. The majority indicated that there were problems in the transfer and accuracy of product information and that high-level system attributes should be included in assessing the impact of design changes. This supports the need for a DSS, that includes multiple high-level attributes.

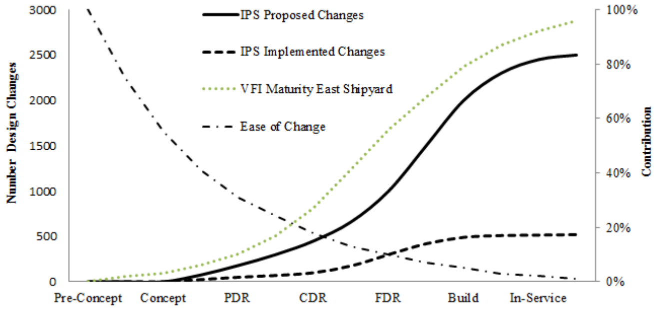

Fig. 11 Shipyard VFI Maturity Compared to the Knowledge Curve

In better understanding knowledge management and information flow within the project design team, SNA measures are included in the CLD, as depicted in Figure 12. The CLD includes knowledge management, human and social capital, management of design changes, casual relationships, and influencing factors.

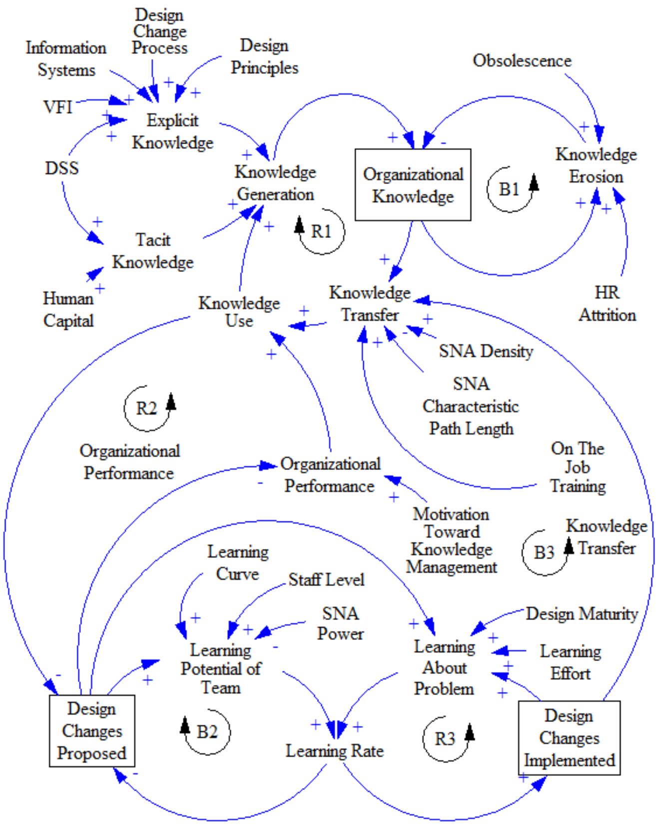

Fig. 12 Shipyard Design Team Causal Loop Diagram for Incorporating the MCDM-IAF, DSS, Knowledge Management, and Design Change Management

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In developing the CLD, the initial state of a knowledge management within the organization is assumed to follow a reinforcing positive loop early in the design cycle. The knowledge growth eventually erodes through a balancing loop that may represent issues in the organization such as human resource attrition and technology obsolescence.

The levers to move the Knowledge curve forward in the design cycle may include increased use of the MCMM-IAF DSS and playing out design change scenarios; other influencing factors such as human capital, a well-defined change process, accurate and mature VFI, design principles, and the quality of information systems are included in the CLD.

It is proposed that the number of team scenarios, played out as part of the MCDM-IAF and DSS, can provide a measure of organizational knowledge. Lessons-learned and typical design changes can also add to the knowledge base. The transfer and use of knowledge in assessing and reducing the number of proposed design changes includes a feedback loop to organizational performance. The learning potential of the team and reducing proposed changes forms a balancing loop. Learning about the proposed design changes and strategizing solutions can increase the learning rate and reinforce the capability to implement design changes. This in turn may enhance knowledge transfer and knowledge use, leading to fewer proposed design changes.

The functionality of the MCDM-IAF presented in the current work was demonstrated though application of the IPS case study and by playing out design change scenarios. This study confirmed the feasibility of the MCDM-IAF and DSS to align multiple disciplines in terms of common capability-based outcome measures and to enhance information and visualization of the variability in attributes throughout the product design life cycle. Integration of the SRM and DSM can promote active risk management and early application of design principles. The six sigma statistical tools and techniques investigated in the current work demonstrated that a common language is possible across multiple disciplines with visualization of variances for non-dimensional design attributes.

SNA of a shipyard design team, for two change scenarios, provided insight into the influence that teams have in the gaming of change scenarios and decision-making. SNA measures, as well as other factors discussed in this paper, were used as inputs into the CLD to help visualize and understand the causal relationships affecting decision-making in design change management.

The typical Knowledge and Ease-of-Change curves appear to reflect the traditional waterfall project management and systems engineering design-build-test approach. The current study proposes that set-based goal-based attribute management and concurrent multi-discipline collaboration through the MCDM-IAF and DSS can provide aspects of agile management that can help better position the Knowledge and Ease-of-Change curves.

In future work, attainable reference data, that may be used to further develop the CLD into a systems dynamic model, includes the typical Knowledge and Ease-of-Change curves, shipyard design team learning curves, shipyard data on the number of design changes, VFI, and Design Maturity. The system dynamics model can provide for systems thinking and a reductionist approach in further validating the usefulness of the MCDM-IAF and DSS in reducing design costs.

IV. Literature Survey

References provided in this paper form a literature review. This review investigated the various systems engineering and program management models that form part of the proposed MCDM-IAF and DSS. Review of game theory provided provenance in developing the approach to playing out design change scenarios. Review of SNA and knowledge management theory provided insight into how the Knowledge curve might be moved forward in the design cycle.

References

[1] Baron, C., et al., A Method and Tool to Support the Management of Systems Engineering Projects, Technology Innovation Management Review, 2015.

[2] Behdinan, K., Ruben, P., and Liu, H., Multidisciplinary Design Optimization of Aerospace Systems, Proceedings of the Canadian Engineering Education Association, 2011.

[3] Matthews, M.G., et al., Multi-Attribute Tradespace Exploration for Survivability, 7th Annual Conference on Systems Engineering Research, 2009.

[4] Koha, E., et al., A Technique to Assess The Changeability of Complex Engineering Systems, Journal of Engineering Design, Vol. 24, No. 7, pp. 477–498, 2013.

[5] Clarkson, P., Simons, C., and Eckert, C., Predicting Change Propagation in Complex Design, Transactions of the ASME, Vol. 126, pp. 799-797, 2004.

[6] Levinson, W., and Tumbelty, F., SPC Essentials and Productivity Improvement – A Manufacturing Approach, ASQC Quality Press, Milwaukee, Wisconsin, 2010.

[7] Wise, S., and Fair, D., Innovative Control Charting, Practical Solutions for Today's Manufacturing Environment, ASQ Quality Press, Milwaukee, Wisconsin, pp. 27-38, 1998.

[8] Chalfant, J., Early Stage Design for Electric Ship, Proceedings of the IEEE, Vol. 103, No. 12., 2015.

[9] Morkos, B., Shankar, P., and Summers, J.D., Predicting Requirement Change Propagation Using Higher Order Design Structure Matrices: An Industry Case Study, Clemson Engineering Design Applications and Research (CEDAR), Clemson University TigerPrints, South Carolina, 2012.

[10] Krebs, V., Managing The 21st Century Organization, Institute of Health Record Information and Management Journal, pp. 2-8, 2007.

[11] Solesvik, M., Collaborative Knowledge Management: Case Studies From Ship Design, International Journal Business Information Systems, Vol. 8, No. 2, pp. 131-145, 2001.

[12] Baskerville, R., and Dulipovici, A., The Theoretical Foundations of Knowledge Management, Knowledge Management Research and Practice, Vol. 4, pp. 83-105, 2006.

[13] Sterman, J.D., Business Dynamics: Systems Thinking and Modeling for a Complex World, Irwin McGraw-Hill Inc., Boston, Ed. 1, 2000.

[14] Laverghetta, T., and Brown, A., Dynamics of Naval Ship Design: A Systems Approach, Naval Engineers Journal, Vol. 111, No. 2, pp. 307-324, 1999.

[15] Liang, Z., Yan, L., and Shang, J., Collaborative Multi-disciplinary Decision Making Based on Game Theory in Ship Preliminary Design, J Mar Sci Technol, Vol. 14, pp. 334-344, 2009.

[16] Morris, A.,et al., Assessing The Challenges of Managing Product Design Change Through-Life, Journal of Engineering Design, Vol. 27, Nos. 1-3, pp. 25-49, 2016.

[17] Ramanathan, C., et al., Construction Delays Causing Risks on Time and Cost – a Critical Review, Australasian Journal of Construction Economics and Building, 12 (1), pp. 37-57, 2012.

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