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CO-EVOLUTION OF COMMUNICATION AND SYSTEM PERFORMANCE IN ENGINEERING SYSTEMS DESIGN: A STOCHASTIC NETWORK-BEHAVIOR DYNAMICS MODEL

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ABSTRACT

The socio-technical perspective on engineering system design emphasizes the mutual dynamics between interdisciplinary interactions and system design outcomes. How different disciplines interact with each other depends on technical factors such as design interdependence and system performance. On the other hand, the design outcomes are influenced by social factors such as the frequency of interactions and their distribution. Understanding this co-evolution can lead to not only better behavioral insights, but also efficient communication pathways. In this context, we investigate how *to quantify the temporal influences of social and technical factors on interdisciplinary interactions and their influence on system performance*. We present a stochastic network-behavior dynamics model that quantifies the design interdependence, discipline-specific interaction decisions, the evolution of system performance, as well as their mutual dynamics. We employ two datasets, one of student subjects designing an automotive engine and the other of NASA engineers designing a spacecraft. Then, we apply statistical Bayesian inference to estimate model parameters and compare insights across the two datasets. The results indicate that design interdependence and social network statistics both have strong positive effects on interdisciplinary interactions for the expert and student subjects alike. For the student subjects, an additional modulating effect of system performance on interactions is observed. Inversely, the total number of interactions, irrespective of their discipline-wise distribution, has a weak but statistically significant positive effect on system performance in both cases. However, excessive interactions mirrored with design interdependence and inflexible design space exploration reduce system performance. These insights support the case for open organizational boundaries as a way for increasing interactions and improving system performance.

Keywords: Interdisciplinary Interactions; Systems Design; Network-Behavior Dynamics; Descriptive Analysis

NOMENCLATURE

S Design interdependence matrix
$t_0, t_1, \ldots, t_m, \ldots, t_M$ Equidistant observation times
δ Sampling window, i.e., difference between consecutive observation times $[t_{m-1}, t_m]$ for all $m = 1, \ldots, M$

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τ Smoothing window

$X(t_m)$ Matrix of interdisciplinary interactions counted during interval $[t_{m-1}, t_m]$

$Z(t_m)$ System performance vector averaged during interval $[t_{m-1}, t_m]$

1 Introduction

Most activities in engineering systems design are performed by people in multiple disciplines working concurrently and collaborating with each other [1, 2]. The interdisciplinary interactions influence the systems design outcomes such as system performance, design costs, and on-time completion of projects [3]. The interaction patterns generally vary along dimensions such as the frequency of interactions and the distribution of interactions across disciplines. Improving the system design outcomes requires understanding which factors drive interdisciplinary interactions as well as understanding which interaction patterns are effective. This understanding can not only provide behavioral insights about designers' decision making, but also lead systems engineers to devise effective communication pathways.

According to some existing models, the patterns of interdisciplinary interactions predict changes in system performance [4, 5, 6, 7, 8]. Such studies mainly utilize social network statistics to represent the mechanisms underlying interactions. However, it is well known that both *social factors* arising from historical interactions and *technical factors* arising from design interdependence (what depends on what) or system performance shape the interactions [2,9,10]. There is a need to establish models of simultaneous effects from both the social and technical factors on interactions, in addition to modeling the effects of resulting interaction patterns on the system performance. A model for this purpose should infer the relative influence of social and technical factors based on empirical observations. This would allow a comparison of influences across different design contexts (tasks, designer expertise, etc.). The model should also capture the temporal co-evolution of interactions and system performance, because the effectiveness of interactions may vary over time [11].

Towards that goal, the research objective of this paper is *to quantify the temporal influences of social and technical factors on interdisciplinary interactions and their influence on system performance.* We hypothesize that this quantification can lead to insights about structuring effective communication pathways. Specifically, the focus is on two types of influences: (i) how different social and technical factors influence discipline-level decisions, such as how much to interact (rate of interactions) and whom to interact with (pairwise interactions), and (ii) how different interaction patterns (e.g. the amount of all interactions or the degree of mirroring between interactions and design interdependence) influence the system performance. We assume that a single decision maker represents a discipline. Our approach consists of a stochastic network-behavior dynamics model, inspired from longitudinal network models [12, 13], to capture the temporal influences. The model represents interactions during any given time period as a network with disciplines as its nodes. The link formation represents discipline-level interaction decisions, whereas the network behavior represents the system performance. We train the model separately on two datasets, one of 40 different student teams designing an automotive engine and the other of six studies by a team of NASA engineers designing a spacecraft. Statistical Bayesian inference is used on both datasets separately to get posterior parameter estimates for the dynamics model.

This work contributes a stochastic model along with behavioral insights and has broader implications for the practice of designing engineering systems. First, the theoretical model trained on empirical observations enables inductive claims about interdisciplinary interactions in a generalized situation. The trained model acts as a generative model of interactions in counterfactual settings, generating potential insights that can be tested using future experiments. Second, the results shed light on the similarities and differences between interaction patterns of the expert NASA engineers and beginning student designers. For instance, comparisons between students' and NASA engineers' system design reveal differences in decisions about how much they interact, but similarities in choosing whom they communicate with. Third, the insights collectively support the case for interactions between highly as well as loosely-coupled subsystems (open organizational boundaries) as a way to improve the performance of the designed system.

The rest of the paper is structured as follows. Section 2 reviews the literature on driving factors behind the interdisciplinary interactions and their effects on system outcomes. We assemble the insights from this literature into five hypotheses to be tested. Section 3 begins with key assumptions and explains mathematical details of the model. Section 4 details the subjects, tasks, and the contexts of concurrent design activities in two datasets. Section 5 interprets of the estimated model parameters from the statistical Bayesian inference for each dataset separately. Section 6 concludes with the summary of key results and contributions and offers suggestions for future research.

2 Related Work and Hypotheses

2.1 Communication Patterns in Engineering Design Teams

Current literature in engineering design points to different types of social and technical factors influencing interdisciplinary interactions and system performance. This section describes those factors along with the evidence of their influence.

2.1.1 Social Factors

Many empirical studies of real-world engineering firms reveal that the interdisciplinary interactions are *structured* and *semantically coherent* even though there exists constant background chatter. Dong et al. [14] observed coherent thinking in team social dynamics based on records of design documents, group- and personal reflections. Snider et al. [15] highlighted that the interdependence between communication and design activities exists in addition to background chatter.

There is also a significant interest in developing agent-based modeling frameworks that represent interactions as network with individuals/disciplines as nodes and edges as interactions [16, 9]. These frameworks are based on the premise that tracking *social network statistics* allows tracking of the progress in design activities. Ultimately, the goal of such frameworks is to model the effects of *individual traits and cognitive biases* on design team formation. For example, McComb et al. [4] model cognitive biases in communication such as preference over own design (self-bias) and organic interaction timing. Ball and Lewis [7] show that network statistics such as eigenvalue centrality, network degree, and betweenness are correlated with the diversity of teams and potentially correlated with design success. Piccollo et al. [6] model persons and design activities as two separate sets of nodes in a bipartite network. They simulate design process failure as targeted removal of people and design activities. Their simulations show that the design process is most vulnerable to failures arising from people. Wu et al. [5] utilize social network analysis to represent collaboration in design teams. They showcase different network statistics to identify team members acting as leaders and team members performing the same activity.

Assuming individuals are the agents driving interdisciplinary interactions, we can consider alternative models of their decision behaviors. Two primary models are the reciprocity model, based on the reciprocity between two individuals [17, 18], and the popularity model, based on the popularity of individuals [19]. In the context of engineering systems design, these models translate into the following hypotheses.

Hypothesis 1a *The larger the interactions between two disciplines in past (i.e. reciprocity), the more likely they will interact in future.*

Hypothesis 1b *The larger the overall interactions by a discipline in past (i.e. popularity), the more likely that the discipline attracts interactions from other disciplines in future.*

2.1.2 Technical Factors

Design interdependence of subsystems significantly influences how much and with whom respective disciplines interact. In complex systems design tasks, multiple disciplines/designers communicate to match the technical interfaces between their respective subsystems [9]. Since such tasks are intractable [20], the mirroring of interactions with the design interdependence is necessary to manage complexity in complex system design [21]. That is, ties should exist between subsystems that are dependent on each other because of shared design variables, design constraints or requirements. This is popularly known as the "mirroring hypothesis". Theoretical approaches for evaluating mirroring involve the use of the "design structure matrix" (DSM) [22, 23]. For instance, a DSM embodying design interdependence between subsystems may be called a "technical DSM," and a DSM embodying interactions may be called an "interaction DSM". Theoretical frameworks to evaluate the fit between technical and interaction DSMs are recently developed [24, 25]. The evaluation of this fit can identify missed interaction opportunities, and thus identifying the need for new communication pathways.

Hypothesis 2: *The number of shared design variables (design interdependence) between a pair of disciplines increases the number of interactions between them.*

A relatively unexplored factor influencing the interdisciplinary interactions is *the evolving state of system performance*. Disciplines/designers communicate for the purposes of clarifying problem specifications and background, resolving newly arising issues, and supporting detailed managerial understanding [2, 15, 8]. Since the overarching goal is to improve system performance outcomes, whenever design inconsistencies or issues arise (i.e. system performance drops), disciplines engage in design dialogue to resolve those issues.

Hypothesis 3: *Lower system performance increases the likelihood of future interdisciplinary interactions.*

2.2 Impact of Communication Patterns on the System Performance

The inverse problem of finding driving factors behind interaction patterns is to identify specific patterns that improve the system performance. A number of studies suggest a positive impact of *the amount of interactions* on system performance. Interactions are important for resolving design inconsistencies [8] and building consensus [2].

Hypothesis 4: *A larger number of interdisciplinary interactions increases the likelihood of improvements in system performance over time.*

Despite its benefits, too many or too few interactions result in imbalance of resources allocated to interactions versus design exploration [26]. Quantifying the effects of interaction amounts can help identify the "sweet spot" between the two extremes. Some studies investigate the adoption of *technical-communication mirroring* as a way to improve performance outcomes in industry studies [21]. According to these studies, the mirroring has mixed effects. Colfer and Baldwin [21] find that the mirroring is prevalent in industrial organizations and firms, but partial mirroring whereby disciplines may break down organizational barriers and form new ones results in superior performance outcomes. For open organizations, full mirroring is absent which the authors associate with digital modes of interactions that enable coordination. For engineering design teams alike, the results suggest that increased knowledge grounding could have detrimental effects when teams are faced with tasks that fall outside the team's expertise [27]. These studies imply that the perfect mirroring between disciplines' interactions and their design interdependence is less preferable than partial mirroring whereby a suitable fraction of interactions exist between disciplines with weak design interdependence. This allows disciplines to collectively tackle unforeseen design issues that arise during the design process.

We extrapolate the influence of moderated the technical-communication mirroring to the changes in the overall system performance, as outlined by the following hypothesis. Note that since the technical-communication mirroring is always partial, we use the terminology of strongly mirrored interactions to represent interactions between highly-interdependent disciplines.

Hypothesis H5: *An excessive number of strongly mirrored interactions reduces the system performance over time.*

In short, different studies focus on social and technical factors but rarely incorporate simultaneous effects of those factors in empirical observations and modeling effort. This paper builds modeling and empirical support towards a comprehensive inductive framework, with the purpose of explaining interdisciplinary interactions and evaluating the effectiveness of various interaction patterns. Section 3 details the proposed theoretical model and its embodied structural assumptions.

3 Stochastic Network-Behavior Dynamics Model

This section presents details of key assumptions behind the stochastic network-behavior dynamics model.

Engineering systems design is a complex process that involves multiple disciplines. Two main features of this process are: the interdependence between design variables and the aggregation of subsystem-level objectives. These features necessitate communication between disciplines. The collective goal of disciplines is to design systems that maximize certain objectives. Individually, a discipline optimizes a subsystem by evaluating subsystem-level objectives for different values of design variables, which are aggregated into the system level objectives. In most cases, different subsystems share varying number of design variables between one another. Through design evaluations, a discipline finds how a design variable affects subsystem-level objectives and selects a suitable value.

Given this complexity, analytical modeling of a systems design process requires that we place certain assumptions of the nature of design exploration and interdisciplinary interactions. We consider that a systems design scenario involves N disciplines. Each discipline is responsible for deciding a *fixed* set of design variables. The interdependence of design variables between disciplines is a $N \times N$ matrix S (*design interdependence*) whose element s_{ij} represents the number of shared variables between disciplines i and j for all $i, j (\neq i) = 1, 2, \ldots, N$.

We assume that every discipline repeats two decisions: (i) deciding how much to interact and (ii) whom to interact with. The interdisciplinary interactions are a result of decisions made by disciplines (i.e., communication is an *actor-based process*). Further, there can be only bidirectional interactions between any two disciplines, which we call *pairwise interactions*. When making a decision, we assume that every discipline tries to maximize an unobserved utility, and selects the discipline that maximizes this utility. Also, pairwise interactions are *non-hierarchical* meaning that interacting disciplines can have any role, e.g., core designer, systems engineer, and customer. Mathematically, an $N \times N$ matrix $X(t_m)$ assembles observed interactions over time interval $(t_{m-1}, t_m]$. An element of the adjacency matrix $x_{ij}(t_m) \in \mathbb{Z}$ denotes the number of interactions between disciplines i and j during the given time step. A diagonal entry $x_{ii}(t_m)$, if defined, represents discipline i's interaction within itself, e.g., local design iterations.

On the system performance side, each design objective that constitutes the *system* performance vector is discrete but ordered (ordinal) variable whose higher level is preferred over a lower level. A K-dimensional vector $Z(t_m)$ in the vector space $\mathcal{Z}$ denotes the average system performance over time interval $(t_{m-1}, t_m]$.

Clearly, a discipline's decisions are conditional on what is observes (*complete or incomplete information*). When disciplines are co-located, all relevant information is most likely observed by every discipline. On the other hand, the information is partially observed for distributed disciplines. We allow for the possibility of both cases in the model.

Finally, we assume that the temporal dynamics of interdisciplinary interactions and system performance is a result of *the time-homogeneous Markov process*. The Markov assumption means that the conditional distribution of future interactions $\{X(t_{m+1}) \mid t_{m+1} > t_m\}$ given the past and the present for any time t_m depends only on the present state of interactions $X(t_m)$ and the present system performance $Z(t_m)$, in addition to the design interdependence S. Similarly, the distribution of future system performance $\{Z(t_{m+1}) \mid t_{m+1} > t_m\}$ for any time t_m is conditionally dependent on only the present state $X(t_m)$. We assume that these myopic effects are independent of the time (t_m) at which they are evaluated, hence, time-homogeneous. Figure 1 presents a graphical form of this temporal dynamics model.

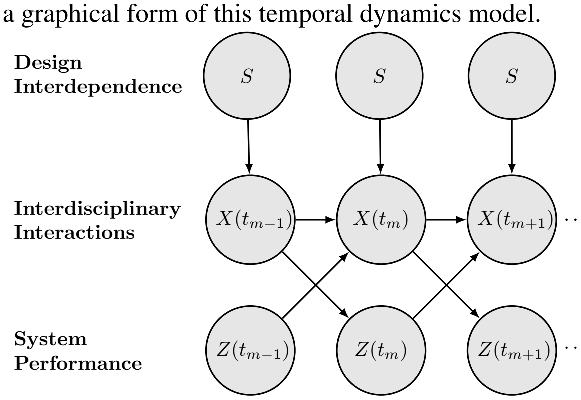


FIGURE 1: A model of communication and design performance dynamics.

3.1 Measuring Interdisciplinary Interactions and System Performance over Time

The observation times are discrete, equidistant times $t_0(=0), t_1, t_2, \dots, t_M$ in a fixed time interval $\mathcal{T} = [0, t_M]$. Interdisciplinary interactions form a finite space $\mathcal{X}$ of networks. A sample network quantifies pairwise interactions (an edge property) in terms of a weighted adjacency matrix. Such network is a directed network if identification of the source and the recipient of each interaction is possible. Accordingly, a time series of interactions forms a discrete stochastic process $\{X(t_m)|\, t_m \in \mathcal{T}\}$ on the network space $\mathcal{X}$. Similarly, the system performance over time is a discrete stochastic process $\{Z(t_m)|\, t_m \in \mathcal{T}\}$ on the vector space $\mathcal{Z}$ where m^{th} time step denotes interval $(t_{m-1}, t_m]$.

A key tuning parameter here is the constant separation between any two consecutive observation times $\delta = t_{m-1} - t_m$, which we call *the sampling window*. The pairwise interactions within a sampling window are simultaneous and independent. A large sampling window δ can misclassify interactions as independent, whereas a small δ would thinly scatter interactions between observation times. We also redefine a time-series by taking a moving average over every τ consecutive time steps, where τ is called *the smoothing window*. The moving average time-series smooths out noisy variations from observations, thereby highlighting essential patterns.

3.2 Modeling the Evolution of Interdisciplinary Interactions

Based on present observations of m^{th} time step, a discipline engages in a sequence of decisions that result in future interactions for $m+1^{th}$ time step. These decisions are:

1. Deciding the rate of interaction, and
2. Deciding the choice probability for pairwise interactions.

Such generation of interdisciplinary interactions, a result of explicit choices by individual disciplines. Algorithm 1 summarizes this process.

3.2.1 Deciding the Rate of Interaction

The first decision is how a discipline decides the rate of interaction, i.e., the average number of interactions by the discipline during given time step. A simplest model is to assume a constant rate of interaction. However, in accordance with the assumption of our model in Figure 1, we represent the rate of interaction as a function of the state of system performance $Z(t_m) = \mathbf{z}$. To allow flexibility, the direction of the influence is allowed to be positive or negative. If the influence is negative, the number of interactions increases if the present system performance is low.

Let vector $\boldsymbol{\beta}_c \in \mathbb{R}^K$ represent the effect of present system performance on the frequency of interactions of type c. Parameter $\gamma_c \in \mathbb{R}$ is a constant intercept. Then, the time-variant rate of interaction of type c decided by discipline i is

$$\lambda_{c,i}(t_{m+1}|\boldsymbol{\beta}_c, \gamma_c, \mathbf{z}) = e^{\boldsymbol{\beta}_c \cdot \mathbf{z} + \gamma_c}. \tag{1}$$

Algorithm 1: Steps in deciding the interdisciplinary interactions for a future time step

Result: Interdisciplinary interactions $X(t_{m+1})$ at $m+1^{th}$ time step
Require: Interdisciplinary interactions $X(t_m) = \mathbf{x}$; System performance $Z(t_m) = \mathbf{z}$; Design interdependence S at m^{th} time step
for *Interaction type c in set C* **do**
  for *Discipline* $i = 1, 2, \dots, N$ **do**
    Decide the rate of interaction $\lambda_{c,i}(t_{m+1}|\mathbf{z})$;
    Sample the number of interactions $N_{c,i}(t_{m+1}|\mathbf{z}) \sim \text{Poisson}(\lambda_{c,i}(t_{m+1}|\mathbf{z}))$;
    for *Pair ij of type c* **do**
      Decide the choice probability $p = p_{ij}(t_{m+1}|\mathbf{x}, \mathbf{z}, s_{ij})$;
      Sample the number of pairwise interactions $x_{ij}(t_{m+1}) \sim \text{Binomial}(N_{c,i}(t_{m+1}|\mathbf{z}), p)$
    end
  end
end

Here, we assume that discipline i fully observes the present system performance $\mathbf{z}$. If that is not the case, partially observed system performance replaces vector $\mathbf{z}$ in Eq (1). Finally, The number of interactions of type c during the next time step is assumed to be a Poisson distribution given by:

$$N_{c,i}(t_{m+1}|\mathbf{z}) \sim \text{Poisson}(\lambda_{c,i}(t_{m+1}|\mathbf{z})). \tag{2}$$

Here, the number $N_{c,i}(t_{m+1})$ counts all interactions of type c involving discipline i.

3.2.2 Deciding the Choice Probability for Pairwise Interaction

For interaction of certain types (e.g. with peer disciplines) where a discipline need to select one discipline out of multiple, we assume that the discipline assigns choice probabilities. Modeling the choice probability requires representation of a specific mechanism by which a discipline chooses whom to interact with.

We assume that discipline i has unobserved utility in communicating with others which it tries to maximize. In general, there could be multiple network statistics dependent on the present adjacency matrix $X(t_m) = \mathbf{x}$. We denote the vector of network statistics as $\mathbf{f}_i(\mathbf{x}) = \{f_{i1}(\mathbf{x}), f_{i2}(\mathbf{x}), \dots, f_{iL}(\mathbf{x})\}$. Specifically, we consider two network statistics. First, nodal popularity statistic measures the total incoming degree of the disciplines that discipline i is connected to. It is mathematically given by $f_{i,1}(\mathbf{x}) = \sum_{j \neq i} \mathbf{1}_{x_{ij}>0} \sum_{h \neq j} x_{hj}$, where indicator function $\mathbf{1}_{x_{ij}>0}$ is 1 if x_{ij} is a positive integer and 0 otherwise. Then, a positive parameter of nodal popularity would imply that disciplines with high incoming interactions in the present are likely to be chosen for more interactions in the future. Second, the pairwise reciprocity statistic measures the number of mutually matched incoming and outgoing links with the connected disciplines, $f_{i,2}(\mathbf{x}) = \sum_{j\neq i}\min\{x_{ij}, x_{ji}\}$. A positive parameter associated with the reciprocity would imply that future interactions occur between disciplines are that interacting in present. Finally, in accordance with the mirroring hypotheses, discipline i would prefer to communicate with others that share higher design interdependence $S = \{s_{ij}\}$ with it.

By interacting with discipline j, discipline i can potentially change its dyadic network statistics by amount $\mathbf{f}_i(\Delta_{ij}\mathbf{x}) - \mathbf{f}_i(\mathbf{x})$, where operator Δ_{ij} reflects the single change due to an interaction added to element x_{ij}. Similarly, by interacting with discipline j, discipline i increases its utility by amount proportional to design interdependence s_{ij}. Then, the projected change in utility of discipline i by interacting with discipline j is:

$$U_{ij}(\mathbf{x}) = \boldsymbol{\beta}\cdot(\mathbf{f}_i(\Delta_{ij}\mathbf{x}) - \mathbf{f}_i(\mathbf{x})) + \gamma s_{ij} + \varepsilon_{ij}, \tag{3}$$

where random parameter ε_{ij} changes between discipline pairs and changes with time (which is assumed implicit to simplify the notation). Parameters $\boldsymbol{\beta} \in \mathbb{R}^L$ and γ represent the relative preferences for network statistics and design interdependence, respectively. For co-located disciplines, discipline i fully observes present interdisciplinary interactions $\mathbf{x}$. For distributed disciplines, partially observed interactions replaces matrix $\mathbf{x}$ in Eq. 3. Note that discipline i's utility in Eq.(3) is different from the the system-discipline design objectives that *all* disciplines supposed to maximize collectively.

Then, the choice probability for discipline i to select a discipline for interaction in the next time step is exponentially proportional to the change in utility in Eq (3). If we consider that ε_{ij} has a standard Logistic distribution, then the probability that discipline i selects discipline j, given that discipline i is interacting, is:

$$p_{ij}(\mathbf{x}, s_{ij}) = \frac{e^{\boldsymbol{\beta}\cdot\mathbf{f}_i(\Delta_{ij}\mathbf{x}) + \gamma s_{ij}}}{\sum_{h\neq i} e^{\boldsymbol{\beta}\cdot\mathbf{f}_i(\Delta_{ih}\mathbf{x}) + \gamma s_{ih}}}. \tag{4}$$

This choice probability function has a multi-logit form similar to multinomial logistic regression and dependent on present state of interactions $\mathbf{x}$ and pairwise design interdependence s_{ij}.

3.3 Modeling the Evolution of System Performance

In the proposed model, future state of system performance $Z(t_{m+1})$ dependence on the present state of observed interdisciplinary interactions $X(t_{m+1}) = \mathbf{x}$. Through larger interactions among the disciplines and partial or substantial rework, the design inconsistencies may get resolved in a long term. The downside of misplaced, inefficient distribution of interactions might be the lost opportunity to recover from design inconsistencies.

Algorithm 2 presents the steps involved in this process. Let vector $N(t_m) \in \mathbb{Z}^C$ denote the *observed* numbers of total interactions through C different types. We assume that the change in a performance component from its present level to a future level is in in accordance with the maximization of an objective function similar to Eq. (3). Note, however, a change in system performance is *not* a matter of conscious choice on part of disciplines and rather the virtue of the discipline's design search decisions, subsystem models, and integration of system-level objectives. Following these assumptions, we define the utility of generating level z for the k^{th}-component of the system performance vector in the next time step $z_k(t_{m+1})$ as:

$$U_k(z) = \boldsymbol{\beta}_k^z \cdot N(t_m)z + \gamma_k^z z + \zeta_k. \tag{5}$$

Here, positive values of effect parameters $\boldsymbol{\beta}_k^z$ imply that large numbers of interactions increase $Z_k(t_{m+1})$. Positive γ_k^z would signify that performance levels are always large in general, where as negative γ_k^z would signify the opposite. Random variable ζ_k is specific to the present time step and design component.

From the set of possible levels $\mathcal{Z}_k$, the temporal dynamics generates a particular level z with the following probability:

$$p_k(z, \mathbf{x}) = \frac{\boldsymbol{\beta}_k^z \cdot N(t_m)z + \gamma_k^z z}{\sum_{q\in\mathcal{Z}_k} \boldsymbol{\beta}_k^z \cdot N(t_m)q + \gamma_k^z q}. \tag{6}$$

This choice probability depends on the present interaction state $\mathbf{x}$. Implicitly, the derivation of Eq.(6) assumes that the random variable ζ_k has a standard logistic distribution.

Algorithm 2: Steps in predicting the system performance for a future time step

Result: System performance $Z(t_{m+1})$ at time step t_{m+1}
Data: Interdisciplinary interactions $X(t_m) = \mathbf{x}$
for *Design objective* $k = 1, 2, \ldots, K$ **do**
  Read observed interactions of different types
   $N(t_m) = \{\sum_{ij\in\text{Type } c} x_{ij}\}_{c\in C}$;
  for *Performance level z in set $\mathcal{Z}_k$* **do**
   Calculate the choice probability $p_k(z, \mathbf{x})$;
  end
  Assemble choice probability vector
   $\mathbf{p}_k = \{p_k(z, \mathbf{x})\}_{z\in\mathcal{Z}}$;
  Sample future performance level
   $z_k(t_{m+1}) \sim \text{Categorical}(\mathcal{Z}_k, \mathbf{p}_k)$
end

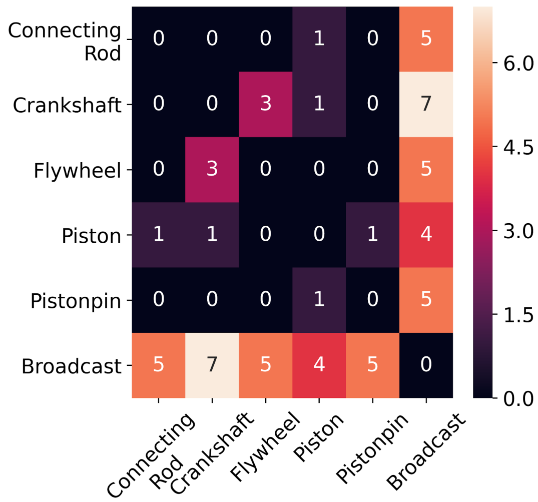
4 Empirical Datasets

As the source of empirical observations, this section describes two empirical datasets, *engine design dataset* and *spacecraft design dataset*. As an overview, Figure 2 presents the disciplines and their interdependence for both datasets (more details in Ref. [11]). Each discipline represents one subsystem.

4.1 Engine Design Dataset

The engine design task involves design of an engine partitioned into five subsystems/disciplines, viz., connecting rod, crankshaft, piston head, flywheel, and piston-pin. One individual fulfills the role of each of discipline. The design of each sub-

(a) Design structure matrix for the engine design problem



(b) Design structure matrix for the spacecraft design problem.

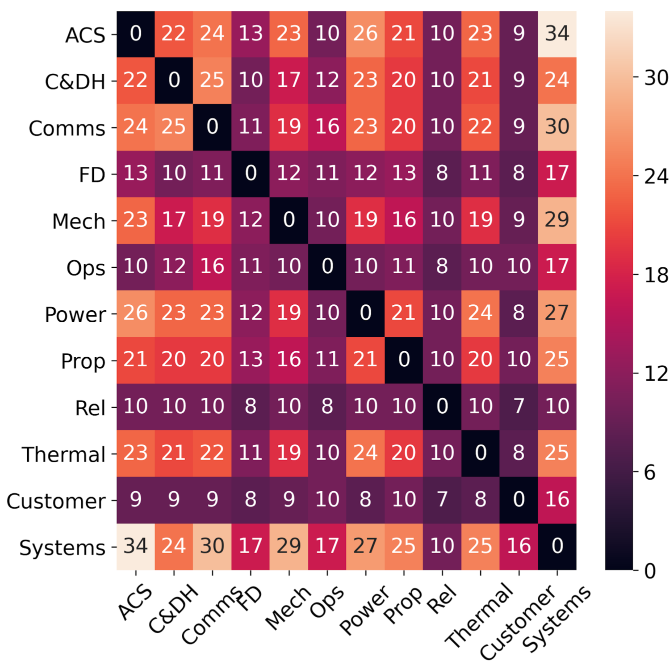


FIGURE 2: Pairwise design interdependencies in the matrix cells represent the number of shared design variables

system requires specification of a set of design parameters while considering the effects of other parameters shared with other subsystems. The system-level design objectives in the experimental task are to minimize the total mass of the engine components and maximize the factor of safety against failure. The total mass is the sum of individual masses, whereas the system-level factor of safety is minimum of individual factors of safety. The performance in both cases is measured in five discrete levels.

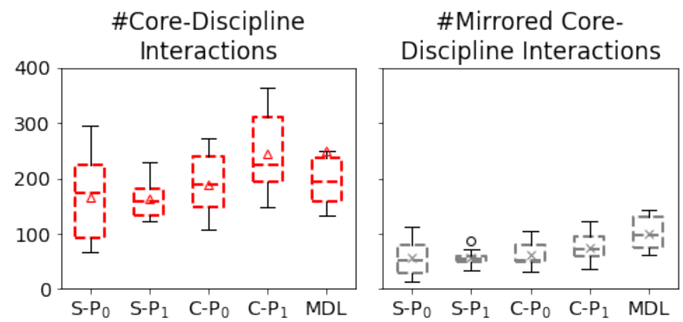


FIGURE 3: The distribution of observed interactions between core disciplines.

Disciplines working on the same project communicate with one another through *one-to-one text messages*. Another component of the team is a shared virtual screen, called "broadcast", that showed the current values of design objectives and design parameters. Since disciplines were distributed and were only allowed one-to-one interactions, the broadcast rule was introduced as an integrative role to facilitate information exchange. The dataset include timestamped interactions between subjects on the same team as well as timestamped values of design objectives (total system mass and factor of safety).

In total, the dataset spans 40 teams, and a total of 200 undergraduate students in mechanical engineering. Each team belongs to one of the four experimental conditions varying in: i) design exploration using simulations on the continuous design space versus a catalog with pre-evaluated design points scattered across the design space, and ii) the global availability of shared design parameter database on the broadcast screen versus no such availability. The factorial design of experiment generates four experiment treatments: i) simulations without a parameter database (S-P_0), ii) simulations with parameter database (S-P_1), iii) catalog search without a parameter database (C-P_0), and iv) catalog search with parameter database is visible (C-P_1).

4.2 Spacecraft Design Dataset

The spacecraft design task involves conceptual design of spacecraft systems with 10 core disciplines and 2 integrative disciplines such as systems engineer and customer. Each core discipline is represented by one engineer, whereas an integrative discipline includes two or more individuals. Such task is conducted through 4-day long studies at the NASA Goddard mission design laboratory (MDL). The dataset includes observations from a total of six studies. For each study, co-located NASA engineers with specialized knowledge of one subsystem design their respective spacecraft subsystems. Additionally, a systems engineer facilitates information interaction between different subsystems. One of the design objectives is to meet customer-specified requirements on the spacecraft dry mass, which is the total mass of individual subsystem designs. Subsystem engineers periodically post their present subsystem mass to a common database acces-

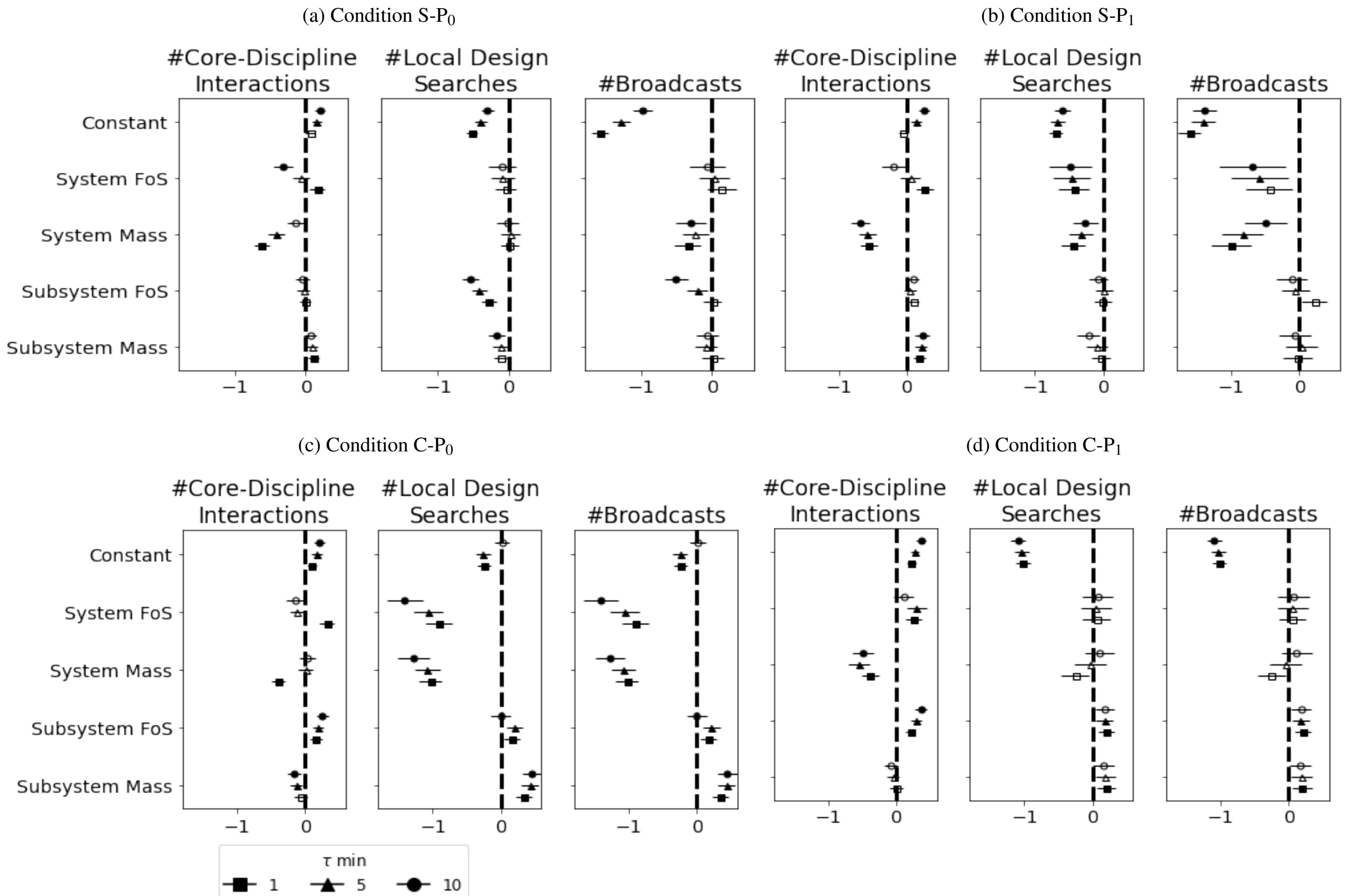


FIGURE 4: Predicting the rate of interactions. The predictor variables (i.e., the performance metrics) are ordinal variables, whose larger values are preferred over smaller values. Estimates denoted by filled points are statistically significant with $p-$value less than 0.01.

sible by others. To introduce consistency with the engine design dataset, we categorize the achieved system performance (spacecraft dry mass) into five discrete levels based on study-specific partitions.

The subjects of each study interact face-to-face for meetings. The face-to-face meetings may include groups of two or more subjects. The spacecraft design dataset converts a group talk into one-to-one undirected pairwise interactions between all those involved.

For each of the six spacecraft design studies, the dataset includes timestamped observations of pairwise interactions, the identities of disciplines involved in each interaction, and the system-level spacecraft dry mass. Most of the six studies have one engineer, mainly the same person, assigned to each subsystem with detailed prior knowledge of their respective spacecraft subsystems and relevant design interdependence.

5 Results and Discussion

The Bayesian inference on the stochastic network-behavior dynamics model provides posterior estimates of model parameters conditional on the time-series observations. The posterior estimates of model parameters represent the effects of independent variables from the past on dependent variables in the present. Examples of independent variables at $(m-1)^{\text{th}}$ timestep are the number of interactions $N(t_{m-1})$, system performance $Z(t_{m-1})$, and constant design interdependence S. In general, an independent variable is a rolling average (in the case of system performance) or rolling sum (in the case of number of interactions) of observations over small duration in past, referred to as smoothing window τ. We assume that τ takes one of three values $\tau = \{\delta, 5\delta, 10\delta\}$, where δ is the sampling period for observations. In the engine design dataset, δ is 1 minute, where as δ is 1 hour for the spacecraft design dataset. The dependent variables are observations from the present t_m such as (i) the rates of interaction $\lambda_c(t_m)$ for interaction types $c = 1,2,\ldots,C$, (ii) pairwise interdisciplinary interaction $X(t_m)$, and (iii) system performance $Z(t_m)$.

We also define a new quantity named *mirrored interactions*. Mirrored interactions are the interactions between highly coupled disciplines in the system design team. Highly-coupled discipline pairs in the engine design problem have one or more shared design variables. In the spacecraft design problem, discipline pairs with shared design variables 16 or more are considered to be highly-coupled.

5.1 Operationalization of Hypotheses

5.2 Model Training

We train the stochastic network-behavior dynamics model for the engine design and the spacecraft design datasets independently. Different experimental conditions in the engine design dataset are also treated independently. In each case, training data corresponds to approximately 90% of teams. The trained model is validated against the data of remaining teams, forming nearly 10% hold-out data. We assign a standard normal distribution as the prior distribution for every model parameter. The likelihood functions for three dependent variables are given by Eqs. 2, 4, and 6.

5.3 Descriptive Statistics

Figure 3 presents aggregated statistics (mean and variance) of the number of interdisciplinary interactions. In the engine design experiment, the amount of total interactions (as well as mirrored interactions) is larger when catalogs are used for design exploration (conditions C-P_0 and C-P_1) than when designs are sequentially evaluated on a continuous design space (conditions S-P_0 and S-P_1). Also, the ratio of mirrored interactions to total interactions in the NASA MDL teams is approximately 80%. However, the same ratio is relatively small across all conditions

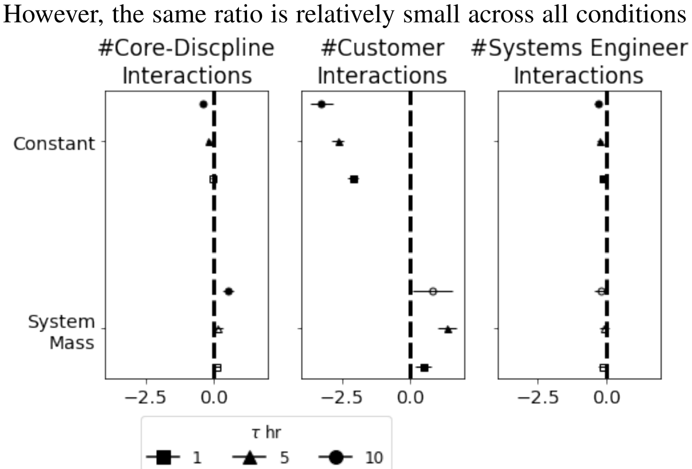


FIGURE 5: Predicting the rate of interactions through different channels. Estimates denoted by filled points are statistically significant with $p-$value less than 0.01.

in the engine design dataset ($50-70\%$). This potentially highlights the effect due to differences in domain expertise of NASA engineers and the student students.

5.4 Effects on the Rate of Interactions

Figures 6 and 7 summarize the effects of system performance from past on the present rate of interaction. Positive estimates denote positive effects whereas the negative estimates represent negative effects. Estimates denoted with filled points are statistically significant with $p-$value less than 0.01.

In the engine design experiment, the past system or subsystem performance levels a have negative effect on the present number of local design searches (i.e., hypothesis H3 is supported). This effect is statistically significant in conditions S-P_0, S-P_1 and C-P_0, except condition C-P_1. In condition C-P_1, the design space exploration is efficient due to the availability of catalogs and the global availability of design parameters, which may not necessitate larger design iterations.

Further, the past system mass performance has a negative effect on the present rate of text-based interactions between core disciplines (i.e., hypothesis H3 is supported). Low performance levels of the system mass in the past drive more one-to-one textual interactions in the preset, highlighting the subjects' focus on the system mass levels. In condition C-P_0, the observed negative effect is only significant between consecutive time steps ($\tau = 1$ minute), suggesting only a myopic effect.

In the NASA studies, Figure 7 reveals that the system mass performance has a positive effect on the face-to-face interactions over longer term ($\tau = 10$ hours) (i.e. hypothesis H3 is *not* supported). Good system performance from the past fuels more face-to-face interactions in long term ($\tau = 10$ hours), unlike in the student teams. The NASA engineers' continued interdisciplinary dialogue may be due to their incentives of maintaining the overall integrity of the spacecraft design, beyond just reducing the spacecraft mass. Whereas, the student subjects' incentives are aligned with maximizing only the system performance based on the system-level mass and FoS.

5.5 Effects on Pairwise Interdisciplinary Interactions

For the students' engine design tasks, Figure 8 reveals that the design interdependence and the pairwise reciprocity are statistically significant predictors of how a discipline chooses another discipline for text-based interactions (hypotheses H1 and H2 are supported). That is, the number of shared design variables is positively correlated with pairwise-specific interactions. This positive effect is stronger in the conditions S-P_0 and S-P_1 than in conditions C-P_0 and C-P_1, possibly because of larger text-based interactions in S conditions. Additionally, the strong influence of the pairwise reciprocity, i.e., the inclination to interact with disciplines with history of interactions, signifies the role of social factors in driving interdisciplinary interactions. The effect of nodewise popularity is small and statistically insignificant

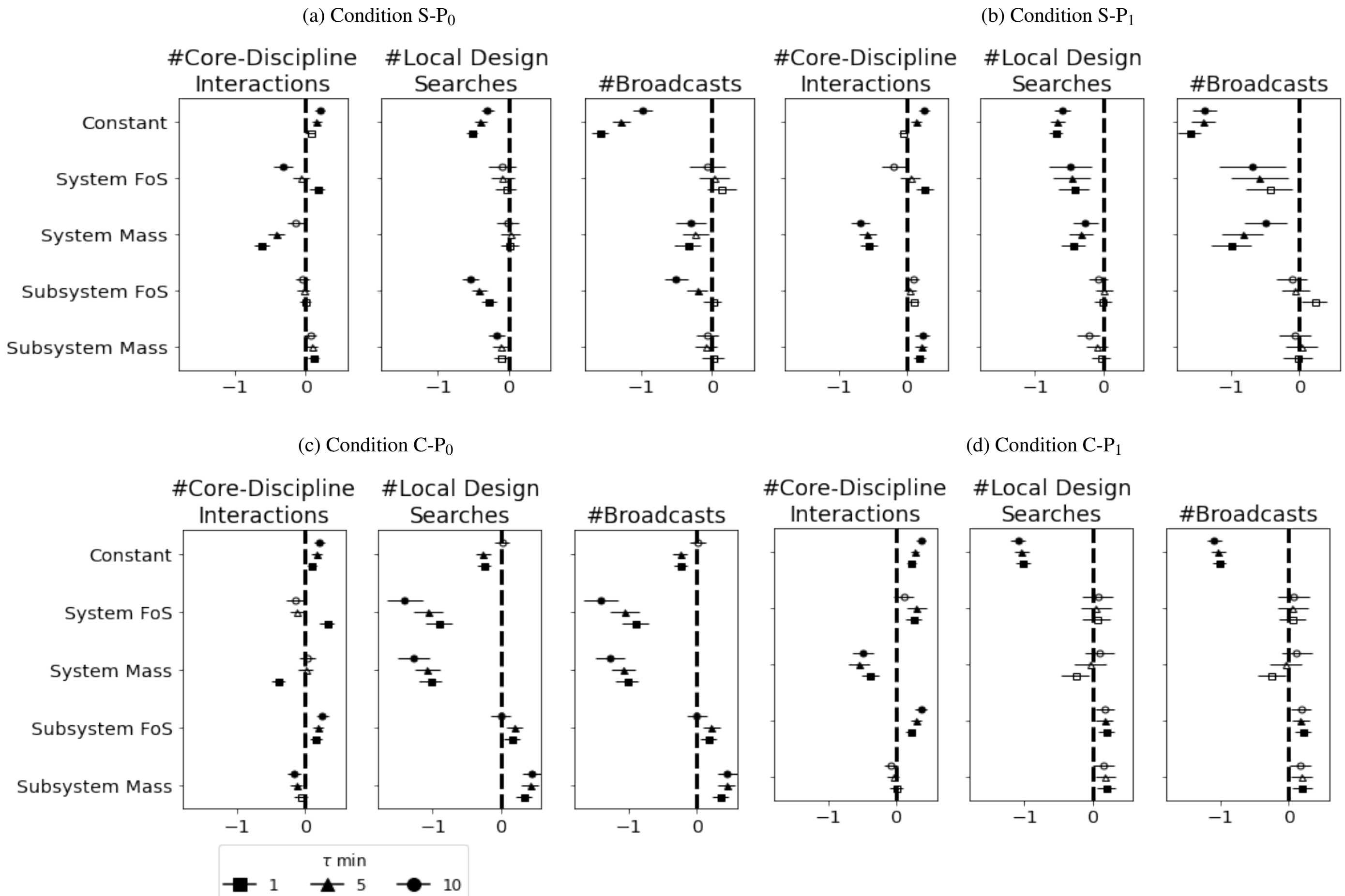


FIGURE 6: Predicting different rates of interactions from the past performance levels averaged over past τ time period, for the student engine design dataset. The performance levels are ordered discrete whose larger values are preferred over smaller values. The points represent mean estimates and the bars capture the 5^{th} and 95^{th} percentile bounds. The positive estimates represent positive influence whereas the negative estimates represent negative influence. The filled points are statistically significant with $p-$value< 0.01.

which is likely because the disciplines in the engine design task are not co-located. Their interdisciplinary interactions are text-based and not observable to all.

According to Figure 9, for the NASA MDL studies, the design interdependence, nodewise popularity, and pairwise reciprocity all have statistically significant effects (hypotheses H1 and H2 are supported). As observed, both technical and social factors drive the interdisciplinary interactions. These effects may imply that the NASA MDL disciplines first interact with the expected peers, as guided by the design interdependence, and then realize there are other critical disciplines. In hindsight, we know that certain NASA MDL disciplines have regular interactions and are even co-located to support that, thus increasing pairwise reciprocity. Whereas, centralized interactions, as modeled by nodal popularity, are more likely for people like mechanical design and mission planning engineers because of their functional roles in the design process. Note that the analysis considers only the core disciplines excluding integrative disciplines such as customers and systems engineers (and broadcast from student teams).

5.6 Effects on System Performance Changes

As Figure 10 suggests, the effects of amount of interactions on the system performance are small across all conditions in the engine design dataset (hypothesis H4 is partially supported). Consistently, the number of text-based interactions by core disciplines has a small but significant positive impact on *the system factor of safety (FoS)*. However, the mirrored interactions are *inversely* correlated with the system performance, especially in the conditions S-P_0 and S-P_1. On the other hand, condition C-P_0 has a positive effect. Thus, hypothesis H5 is partially supported. In

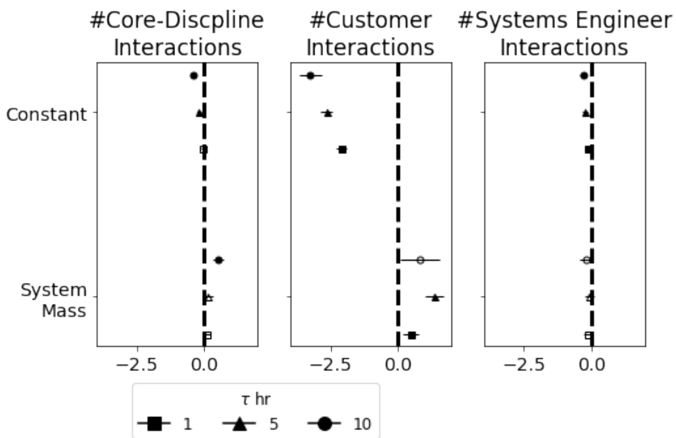


FIGURE 7: Predicting the rates of interactions from the past performance levels averaged over τ time period, for the NASA spacecraft design dataset. The estimates denoted by filled points are statistically significant with $p-$value< 0.01.

condition C-P_0, design variables can only be exchanged through text-based messages without the broadcast. Given lack of alternative channels, sharing such information through interactions can be beneficial.

The number of local design searches also has a negative correlation with system performance, e.g., the system factor of safety. Larger design iterations lead to identification of new design inconsistencies, however, the student subjects' fail to resolve those inconsistencies. The problem complexity (the ruggedness of design space) and the inability to go back to historic system designs might also play roles in weak effects of communication and negative effects of local design searches.

On the other hand, Figure 11 suggests that for the NASA engineers designing a spacecraft system, the number of interactions between core disciplines has a strong and statistically significant effect on the system performance over the long term (τ = 10 hours) (hypothesis H4 is supported). This is likely because a complex system such as a spacecraft may require longer discussions to achieve meaningful improvement in the system performance. On the other hand, too many mirrored interactions result in immediate reduction in the system mass performance (τ = 1 hour) (hypothesis H5 is supported). These observations are consistent with the findings of the student teams, and likely reflect the negative influence (even if it a small effect) on too much grounding by design interdependence.

5.7 Model Validation

We also perform visual checks of model predictions against the observed data and identify following limitations.

1. The models predicts the average number of interactions and associated variance over longer duration much better than the trends over short time duration.
2. The changes in the rates of interactions and system performance are not entirely described by social and technical predictor factors but occur explicitly due to the factor of time. For example, the number of customer interactions in the spacecraft dataset are large initially and reduce to 0 over time. There is also increased interactions by all disciplines towards the end in the spacecraft design task, due to to a tag-up event where the disciplines reconvene to verify their designs.
3. Model fit is poor for predictions of system performance changes. The present number of core-interactions are weak, although significant, predictors of the system performance, as seen from Figure 10. Future work should consider the content of interdisciplinary interactions as a predictor of system performance.

6 Conclusion

This paper presents a quantitative approach combining stochastic network-behavior dynamics model and empirical observations to represent causes and effects of interdisciplinary interactions. The results suggest that there are similarities and differences in how social and technical factors influence the interdisciplinary interactions in the student engine design teams and the spacecraft design studies by the NASA MDL team. These results are summarized according to the stated hypotheses below:

1. Hypothesis H1a and H1b: Social network statistics such as pairwise reciprocity (for both cases) and nodal popularity (for NASA MDL studies only) are strong drivers of pairwise interdisciplinary interactions. This suggests an inherent importance of some disciplines, which is not captured by design interdependence.
2. Hypothesis H2: Pairwise interactions are proportional to the design interdependence, measured by the number of shared variables. This correlation is stronger for NASA spacecraft design studies compared to the student engine design teams.
3. Hypotheses H3: The student subjects modulate the rate of interactions against the levels of system performance, whereas this effect is not significant for interactions among the NASA engineers.
4. Hypotheses H4/H5: The amount of interdisciplinary interactions has a positive impact on system performance in the NASA spacecraft design studies but only over a *long time period*. Additionally, the number of mirrored interactions has a negative effect on the changes in the system performance in the NASA MDL studies over *short time period*. These effects are not always statistically significant in the student engine design teams.

The results highlight the importance of interdisciplinary interactions for collective knowledge discovery in engineering system design. Social and technical driving factors emphasize the socio-technical perspective of interdisciplinary interactions [28]. We find that the number of total interactions, irrespective of how they are distributed, are positively correlated with system perfor-

(a) Condition S-P_0 (b) Condition S-P_1 (c) Condition C-P_0 (d) Condition C-P_1

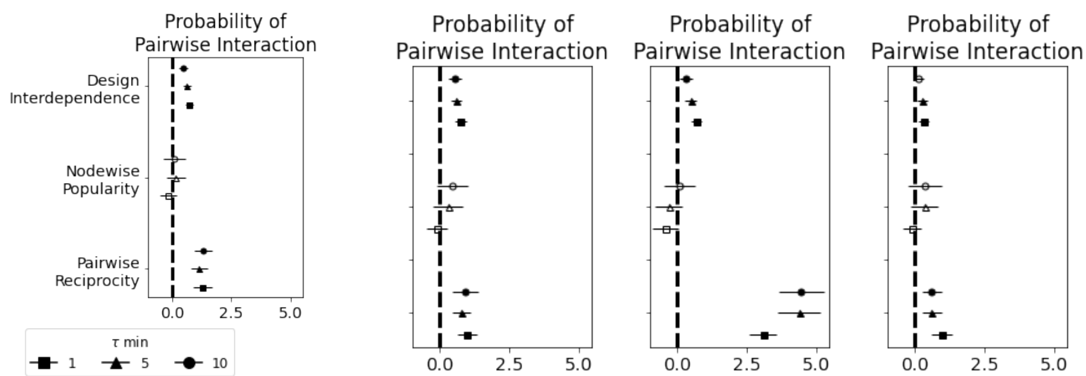


FIGURE 8: Mean and standard deviations for the simultaneous effects of social network statistics from past τ time period & design interdependence on pairwise interdisciplinary interactions, for the student engine design dataset. The estimates denoted by filled points are statistically significant with $p-$value< 0.01.

mance. It is therefore important to facilitate interactions through open communication paths between disciplines. One artifact of managing such interactions and associated complexity has been the mirroring between interactions (organizational structure) and design interdependence (product structure). However, too much grounding of interactions on technical interfaces may hinder potential performance improvement [21,29].

The results support the case for flexibility and improvisation. We observe that the total amount of interactions are larger in conditions C-P_0 and C-P_1 with design catalogs than in conditions S-P_0 and S-P_1 without catalogs. The flexibility in system design, e.g. through design catalogs, shifts a designer's attention from evaluating and planning design evaluations (local search) to

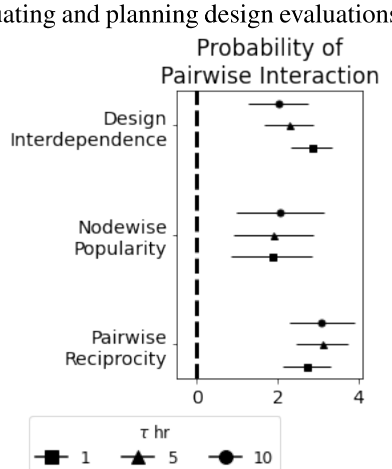


FIGURE 9: The simultaneous effects of social network statistics from past τ time period & design interdependence on pairwise interdisciplinary interactions, for the NASA spacecraft design dataset.

interactions with other disciplines. These findings also demonstrate that the statistical Bayesian inference methodology for inferring the optimal structure of interdisciplinary interactions. Future work can support the development of a quantitative decision support tool based on the stochastic network-behavior dynamics model to assess the structure and improve efficiency of interdisciplinary interactions.

There is potential for improving the present stochastic network-behavior dynamics model and addressing certain limitations. The model only captures time-homogeneous effects but the temporal evolution of interdisciplinary interactions is likely to be due to time-dependent factors such as problem clarification in the early stage or tag-up towards the end. Also, the model considers non-hierarchical interactions between disciplines but there is scope for analyzing hierarchical interactions between managers and designers, possibly by extending the present model to the principal-agent problem [30, 31]. Finally, the present study considers individual-independent and role-independent effects for modeling interdisciplinary interactions. Many studies suggest that leader behaviors displaced by “connectors”, “gatekeepers”, and “horizontal weavers” drive the success of interdisciplinary interactions [32,5]. Future research could investigate the correlation between different social, technical factors and leader behavior and quantify how the degree of leader behavior influences system performance outcomes.

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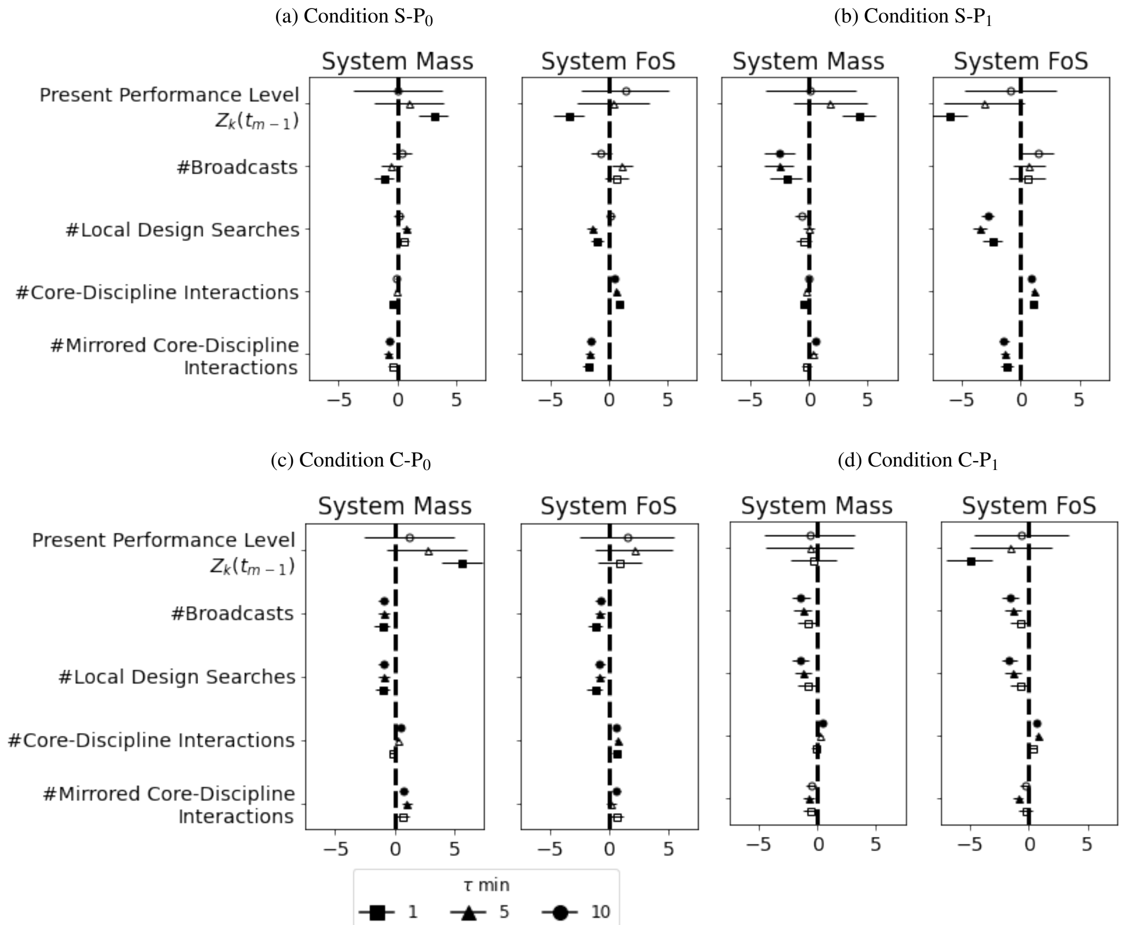

FIGURE 10: Mean and standard deviations for the effects of various interactions amounts counted over past τ time period on system performance, for the student engine design dataset

REFERENCES

[1] Vroom, V. H., and Jago, A. G., 1974. "Decision making as a social process: Normative and descriptive models of leader behavior*". *Decision Sciences,* **5**(4), pp. 743–769.

[2] Bucciarelli, L. L., and Bucciarelli, L. L., 1994. *Designing engineers*. MIT press.

[3] Kvan, T., 2000. "Collaborative design: what is it?". *Automation in construction,* **9**(4), pp. 409–415.

[4] McComb, C., Cagan, J., and Kotovsky, K., 2015. "Lifting the veil: Drawing insights about design teams from a cognitively-inspired computational model". *Design Studies,* **40**, pp. 119–142.

[5] Wu, D., Rosen, D. W., Panchal, J. H., and Schaefer, D., 2016. "Understanding communication and collaboration in social product development through social network analysis". *Journal of Computing and Information Science in Engineering,* **16**(1).

[6] Piccolo, S. A., Lehmann, S., and Maier, A., 2018. "Design process robustness: a bipartite network analysis reveals the central importance of people". *Design Science,* **4**.

[7] Ball, Z., and Lewis, K., 2018. "Observing network characteristics in mass collaboration design projects". *Design Science,* **4**.

[8] Meluso, J., Austin-Breneman, J., and Shaw, L., 2019. "An agent-based model of miscommunication in complex system engineering organizations". *IEEE Systems Journal,* **14**(3), pp. 3463–3474.

[9] Sosa, M. E., Eppinger, S. D., and Rowles, C. M., 2004. "The misalignment of product architecture and organizational structure in complex product development". *Management science,* **50**(12), pp. 1674–1689.

[10] Piccolo, S. A., Maier, A. M., Lehmann, S., and McMahon, C. A., 2019. "Iterations as the result of social and technical factors: empirical evidence from a large-scale design

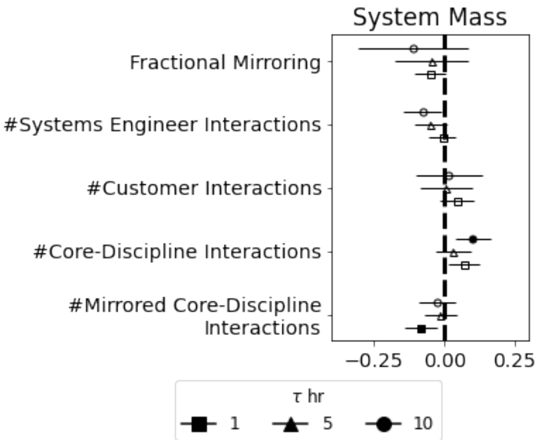

FIGURE 11: The effects of various interaction amounts counted over past τ time period on system performance, for the NASA spacecraft design dataset

project". *Research in Engineering Design,* **30**(2), pp. 251–270.

[11] Chaudhari, A. M., Gralla, E. L., Szajnfarber, Z., Grogan, P. T., and Panchal, J. H., 2020. "Designing representative model worlds to study socio-technical phenomena: A case study of communication patterns in engineering systems design". *Journal of Mechanical Design,* **142**(12).

[12] Snijders, T. A., 2005. "Models for longitudinal network data". *Models and methods in social network analysis,* **1**, pp. 215–247.

[13] Snijders, T. A., Steglich, C. E., and Schweinberger, M., 2007. "Modeling the co-evolution of networks and behavior". *Longitudinal models in the behavioral and related sciences,* **31**(4), pp. 41–71.

[14] Dong, A., Hill, A. W., and Agogino, A. M., 2004. "A document analysis method for characterizing design team performance". *J. Mech. Des.,* **126**(3), pp. 378–385.

[15] Snider, C., Škec, S., Gopsill, J., and Hicks, B., 2017. "The characterisation of engineering activity through email communication and content dynamics, for support of engineering project management". *Design Science,* **3**.

[16] Van den Bulte, C., and Moenaert, R. K., 1998. "The effects of r&d team co-location on communication patterns among r&d, marketing, and manufacturing". *Management science,* **44**(11-part-2), pp. S1–S18.

[17] Wasserman, S. S., 1980. "A stochastic model for directed graphs with transition rates determined by reciprocity". *Sociological methodology,* **11**, pp. 392–412.

[18] Leenders, R. T. A., 1995. "Models for network dynamics: A markovian framework". *Journal of Mathematical Sociology,* **20**(1), pp. 1–21.

[19] Wasserman, S., 1980. "Analyzing social networks as stochastic processes". *Journal of the American statistical association,* **75**(370), pp. 280–294.

[20] Chapman, W. L., Rozenblit, J., and Bahill, A. T., 2001. "System design is an np-complete problem". *Systems Engineering,* **4**(3), pp. 222–229.

[21] Colfer, L., Baldwin, C. Y., et al., 2010. "The mirroring hypothesis: Theory, evidence and exceptions". *Harvard Business School Finance Working Paper*(10-058).

[22] Smith, R. P., and Eppinger, S. D., 1997. "Identifying controlling features of engineering design iteration". *Management science,* **43**(3), pp. 276–293.

[23] Eppinger, S. D., and Browning, T. R., 2012. *Design structure matrix methods and applications*. MIT press.

[24] Szajnfarber, Z., and Gralla, E., 2018. "A framework for measuring the "fit" between product and organizational architectures". In *Disciplinary Convergence in Systems Engineering Research*. Springer, pp. 483–499.

[25] Forsythe, C., Joseph, N., Szajnfarber, Z., and Gralla, E., 2019. "Visualizing communication patterns in design teams over time". In *Systems Engineering in Context*. Springer, pp. 449–461.

[26] Sosa, M. E., Eppinger, S. D., Pich, M., McKendrick, D. G., and Stout, S. K., 2002. "Factors that influence technical communication in distributed product development: an empirical study in the telecommunications industry". *IEEE transactions on engineering management,* **49**(1), pp. 45–58.

[27] Perišić, M. M., Štorga, M., and Gero, J. S., 2018. "Exploring the effect of experience on team behavior: A computational approach". In International Conference on-Design Computing and Cognition, Springer, pp. 595–612.

[28] McGowan, A.-M. R., Daly, S., Baker, W., Papalambros, P., and Seifert, C., 2013. "A socio-technical perspective on interdisciplinary interactions during the development of complex engineered systems". *Procedia Computer Science,* **16**, pp. 1142–1151.

[29] Vrolijk, A., and Szajnfarber, Z., 2015. "When policy structures technology: Balancing upfront decomposition and in-process coordination in europe s decentralized space technology ecosystem". *Acta Astronautica,* **106**, pp. 33–46.

[30] Vermillion, S. D., and Malak, R. J., 2015. "Using a principal-agent model to investigate delegation in systems engineering". In International Design Engineering Technical Conferences, Vol. 57052, ASME, p. V01BT02A046.

[31] Safarkhani, S., Bilionis, I., and Panchal, J. H., 2018. "Understanding the effect of task complexity and problem-solving skills on the design performance of agents in systems engineering". Vol. 2A: 44th Design Automation Conference. V02AT03A060.

[32] McGowan, A.-M. R., Seifert, C. M., and Papalambros, P. Y., 2012. "Organizational influences on interdisciplinary interactions during research and design of large-scale complex engineered systems".