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Interaction Value Analysis: When Structured Communication Benefits Organizations

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Abstract. We present a mathematical model that explains and predicts the value that a management-defined communication structure can add to an organization composed of individuals with universal access to each other. We reduce the problem of optimizing organizational structure to a multiple-player non-cooperative game where players allocate the scarce resource of their attention among potential interaction partners. We investigate the conditions under which the game has a core – i.e., a confluence of individual optima (Nash equilibrium) that is also optimal for any cooperating coalition. Our interpretation is that business environments where these conditions exist do not benefit from strong management control of communication structure. We note that other combinations of conditions in this model fail to yield a core, even though a single stable Nash equilibrium does exist. The difference between aggregate effectiveness at the Nash equilibrium and the maximal feasible aggregate effectiveness is the value that management can provide through enforcing the globally optimum communication regime. The predictions of this simple model about the conditions that favor more or less structured communications agree surprisingly well with accepted organizational contingency theory.

1. Introduction

Some organizations, such as the military, have always been most effective when highly structured. In spite of profound advances in technology, modern armies still follow some rules and patterns well known to Caesar and most visibly articulated by Clauzewits. Even cell-based urban guerrillas need to obey very stringent rules dictating with whom they may communicate. Though decentralized, those units follow highly structured communication patterns. This contrasts with organizations that tend to thrive better when individuals are free to choose with whom they will communicate. The medical establishment, for example, has displayed dogged resistance by both practitioners and patients to one-size-fits-all rules about when to follow certain procedures. Similarly, highly innovative hi-tech firms have often benefited from spin-offs, start-ups and skunk works (Mintzberg, 1989). Freedom from an old established structure is seen as essential for success in these fields. Internet companies similarly tend to follow, or at least pay lip service to, the unstructured (also known as "ad-hoc") communication paradigm. The ideal presented in the press is one of an organization whose communication and interaction channels are in constant flux in response to individual decisions. "Open Source" software development, where hundreds of programmers execute projects by collaborating with each other based solely on their individual initiative and interest (Dibona et al., 1999), displays an extreme form of this "ad-hoc" mode of organization.

More organizations than ever before can now benefit from less rigid control structures, thanks in part to the advent of cheap means of storing, communicating and cataloging information (Davidow, 1992). We can expect these trends to continue as communication technologies get cheaper, interdependencies become less predictable, and work becomes more fast-paced. In particular, Burton and Obel (1998) and others have observed that some environmental and internal contexts favor loosely structured organizations.

Interaction Value Analysis (IVA) is an idealized model which represents the different contexts catalogued in (Burton and Obel, 1998) using precisely defined idealizations. We use IVA in this paper to suggest a parsimonious rational explanation for why some contexts lend a comparative advantage to organizations with more structured communications, while other contexts do not allow these organizations to derive any benefit from structured communications. We will show that the idealizations employed in IVA allow us to avoid both the problem of a continually increasing number of variables and the problem of multiple interpretations of the same variables. (Mintzberg, 1983; Mintzberg, 1989). The distinction between structured and unstructured organizations is based on knowledge exchange efficiency under different conditions. The conditions are represented using five different dimensions of organizational structure and environment. These dimensions are

- **Diversity**: the number of independent skill types needed in the organization;
- **Differentiation**: the contrast in skill levels between the most skilled and least skilled individuals;
- **Interdependence**: the number of different types of work that need to be carried out in a closely coordinated way in order to have value;
- **Load**: the amount of work relative to resources; and
- **Urgency**: the rate at which work becomes useless if left undone.

The remainder of this paper is organized into five sections. We first lay out the research question and our approach to answering it. We then list some of the areas of past research upon which this model builds. These include Organization Theory, Game Theory, Economics, Queuing theory, and two prior papers in which the concepts underlying Interaction Value Analysis were first introduced. This leads us into section 3, where we elaborate on the mechanics of the model we used to derive the current results. Those results are the subject of section 4, along with examples that illustrate how we interpret the results of the model. We conclude with a summary of findings and suggestions for further research.

1.1. Research Question

Why would organizations want to respond to these different contexts by choosing more or less conformance to structured communication? By focusing exclusively on the value that accrues to an organization from the interactions between its members, we can express the distinctions between different contexts using a simple mathematical representation. Analyzing the aggregate "Interaction Value" under different structures allows us to mathematically reconstruct the rules of thumb observed by (Burton and Obel, 1998). Correspondence between the results of the "Interaction Value Analysis" model and the heuristics of Burton and Obel (1998) serves two goals. First, it validates to some extent the assumptions in the model. More importantly, it demonstrates that a preference for or against structured communication does not have to depend on anything more involved, more intangible, or more human, than the confluence of actions generated by simply defined, utility-seeking agents.

In short, this research presents a deductive model that provides a plausible underlying basis for the empirical findings that some situations favor more structure and others favor less structure.

2. Points of Departure

2.1. Organization Science

Many researchers in the Organizational "Contingency Theory" literature have observed how different types of competitive and technological conditions give one form of organization an advantage over another (Galbraith, 1977; Mintzberg, 1983; Scott, 1992). Burton and Obel (1998) surveyed and compiled this literature and derived general heuristics for diagnosing and designing organizations to fit their contexts. The following factors were proposed as favoring organizations with relatively unstructured communication:

1. **Complex Environment:** The benefits of structure depend on the ability of globally informed planners to make optimizing deci-

sions about who should do what. Complex environments, defined as situations where a large number of variables affects these decisions, confound central planning by making a globally optimized solution process less tractable. In those circumstances, individual solutions to subsets of the problem may be preferable to "non-solutions" to the global problem. (Mintzberg, 1983, p.138, Hypothesis 10); (Burton and Obel, 1998, pp. 180-184, 190-194).

2. **Rapidly Changing Technology:** Information about changes in technology takes time to reach higher levels of management. Hence, when technology is changing frequently, competition will favor organizations that can respond more quickly by having smaller groups that adjust independently, and thus rapidly, to these changes. (Mintzberg, 1983, p.137, Hypothesis 9); (Burton and Obel, 1998, pp. 230-234).

3. **Low threat to organization:** When the continuing existence of an organization is at stake, senior managers refuse to take risks by relinquishing control to the periphery. Lack of structure may lead to fatal errors, and is thus intolerable. Conversely, organizations whose immediate survival is not at stake can take more risks. Specifically, they can allow members to communicate more freely and with less structure. (Mintzberg, 1983, p.141, Hypothesis 12); (Burton and Obel, 1998, p. 184, Prop 6.9).

4. **Uniformly high competence:** When everyone can reach the right decision by virtue of experience, training or ability, then it becomes less important to look to a management structure to impose the right decision. (Mintzberg, 1983, p.254); (Burton and Obel, 1998, p.158, Prop. 5.14).

5. **Well-defined skill sets:** A small number of non-overlapping skill sets makes it easier to rely on lower managers and employees to reach decisions about communication paths that will be as good as, but less costly to define and use than, decisions made by top management. (Burton and Obel, 1998, pp.158-159, Propositions 5.10 & 5.15)

Although the variables listed above certainly contribute to the success of organizations with a low degree of structure, quantifying their measures and impacts for a specific organization remains subjective. The causal relationship thus remains associative and heuristic. Interaction Value Analysis(IVA) contributes to this field by proposing a fundamental mechanism that leads from those observed general conditions to the outcome. The variables that we use in IVA also have the advantage of being relatively objective measures, upon which independent observers can more easily agree.

2.2. Concepts from Game Theory

In the mathematical and economic sense, a game is defined as a situation where

1. Several participants make choices
2. All participants achieve some outcome
3. Each participant attaches preferences to different possible outcomes
4. The outcomes for each participant depend on the choices made by that participant and/or other participants.
5. The effects of choices on outcomes may be deterministic or stochastic, and may be known or unknown to the participants.

A set of choices is "in the core of the game" or "a core allocation" if it displays the property of being immune to modification through the actions of any self-serving coalition. When a core allocation is reached, no individual participant can improve his lot by making a change in his decisions. In addition, no coalition of participants, including the coalition of all participants, can make any improvements to its members' outcomes through a group decision without someone in the coalition ending up worse off. Some games have exactly one allocation in the core; others have more than one.

2.2.1. *Exchange Economies*

A classic example of a game that has a core is the simplified model of a market called an exchange economy. The basic principles can be illustrated with as few as two people in the economy. Consider, for example, a well-stocked spaceship where Jack makes bread and Jill makes wine. Neither commodity is as valuable alone as it is in combination with the other. Both parties can benefit from making exchanges up to a certain point. Fundamental microeconomic theories (Scarf, 1967; Debreu, 1959) state that a core exists and is always reachable as long as

1. Every party's utility for any good always increases with the amount of the good, albeit at a decreasing rate.
2. Every party's utility for a bundle of two goods is higher than the same player's utility for either good alone.

These conditions ensure not only the existence and attainability of a core, but also its uniqueness, provided that the goods are infinitely divisible and the market is large enough. Economists use the phrase "competitive equilibrium" to describe this unique core.

2.2.2. *Prisoners' Dilemma (No Core)*
The most widely cited example of a game with no core is the well-known prisoners' dilemma. Two prisoners are accused of a crime and given the choice of implicating one another or denying the charges. If both choose to "confess", then both get long prison sentences. If both choose to "deny" then they can only be charged with contempt of court and spend a few weeks in jail. But if one donfesses and the other denies , then the collaborator gets to go free and the hold-out gets the maximum punishment. To see that a core fails to exist, we note that both players can form a coalition and help one another by sticking to the "deny" strategy. But then each member of the coalition is tempted to confess and break the coalition, improving his lot even further because he would go free instead of serving time for contempt. But that would not be a stable position because the other player would improve his lot by also confessing and implicating the first. Finally, if both players wind up confessing, they would share a long prison sentence. Although neither would be able to improve his lot alone, a coalition composed of both would be able to retract their plea on appeal and win a short sentence for the two. But of course now we are back where we started, and temptation rears its head. Clearly, every possible outcome is capable of being improved upon by some set of players.

2.2.3. *The case of the vanishing core*
Interaction Value Analysis uses utilities that do not fully conform to the assumptions of economic exchange models. There are therefore some instances of the model where the resulting game comes closer to resembling the Prisoners' Dilemma – in other words, where a core does not exist. Since there are multiple parties in Interaction Value Analysis, there are several ways to partition the set of players, and shifting from one set of alliances to a different set will lead to different equilibrium outcomes.

In this paper, we investigate only two extremes. In what we call the structured organization, all participants belong to one coalition. Players who can improve on their outcome (at the expense of others) by leaving that coalition are prevented from doing so by the management structure. We contrast this to what we call the "unstructured" case, where each player acts alone even if colluding with another player might benefit both. Unless there is a core, coalitions of the full population will eventually collapse in the absence of a regulating structure. We do not consider cases of "partial structure", as the aggregate outcome of such partitions will fall somewhere between the two extremes that we do consider.

3. Methodology

The basic model of Interaction Value Analysis was presented in (Nasrallah and Levitt, 2000), and is based on a social network model initially developed in (Huberman and Hogg, 1995). In this model, people make decisions about how to allocate their time among different interaction partners. The patterns generated by these decisions represent the organization structure. Different structures allow different levels of interaction effectiveness, as will be explained below. Ideally, all interaction attempts succeed in securing an interaction, and all interactions succeed in adding value to the organization. This ideal is impossible to achieve, but some time allocation structures come closer to that ideal than others.

In this investigation, we use a particular Interaction Value matrix based on the ordered preferences of six independent parties, as shown in figure 1

$$
\begin{array}{r c}
 & \begin{array}{cccccc} \text{HR} & \text{Sales} & \text{Manf.} & \text{Mktg.} & \text{Eng.} & \text{Mgmt.} \end{array} \\
\begin{array}{r} \text{HR} \\ \text{Sales} \\ \text{Manf.} \\ \text{Mktg.} \\ \text{Eng.} \\ \text{Mgmt.} \end{array} &
\begin{bmatrix}
2 & 3 & 5 & 4 & 6 & \boxed{1} \\
5 & 2 & 6 & 4 & 3 & \boxed{1} \\
6 & 4 & 2 & 5 & \boxed{1} & 3 \\
3 & 2 & 6 & \boxed{1} & 5 & 4 \\
4 & 5 & \boxed{1} & 3 & 2 & 6 \\
5 & \boxed{1} & 6 & 2 & 4 & 3
\end{bmatrix}
\end{array}
$$

Figure 1. A Ranking matrix for a 6-Party Organization

The basic step in modeling a specific organization (or in setting up an idealized model of all organizations) is to have every member of the organization rank every other member in order of how useful they expect an average interaction with the other member to be. The model loses no generality when we include interactions with self (i.e., working alone) in the rankings. The rankings in figure 1 are linearly independent. Two of the parties performing the rankings (represented by the rows of the matrix) have selected the same party being ranked (represented by the columns of the matrix) as the highest ranked - namely the column labeled as "Management".

Let us now suppose that the rows of the matrix represent ranking systems or criteria, each of which is followed by several individuals. The ranking matrix in figure 1 under this new interpretation becomes an abstraction of any organization where each of a large number of members uses a linear combination of six of independent, equally weighted ranking criteria. The equivalence of the two interpretations follows form basic linear algebra, as explained in (Nasrallah et al., 1998). The "equal weight" idealization allows us to represent diversity as a single number instead of a continuous distribution across the $N \times N$ ranking space. The rankings in the matrix are the first step in representing the organizations we study. Each additional nuance of the model is controlled by a parameter that represents a dimension for specifying context.

3.1. Definitions of Context Parameters

3.1.1. *Diversity*

Ranking criteria are not equally weighted in real situations. The ranking matrix in figure 1, which shows six equally weighted criteria, is also an idealization of any organization whose members rank one another such that one party obtains one third of the top rankings. In this investigation, figure 1 is the core matrix for the high diversity examples. The organization is diverse because no one is preferred by more than one third of the members. In contrast, a matrix of three rows and three columns where one column two ones (top rankings) represent low diversity. Two thirds of the population share the same top preference. This is much closer to zero diversity, which is defined as the acse where all of the population has the same preference. The actual numbers selected (one third and two thirds) are clearly arbitrary, but they are sufficient to illustrate the trend created by the diversity parameter. We repeat below a finding from (Nasrallah et al., 1998) that the incidence of two top rankings for the same member being ranked is combinatorically the most likely outcome for groups of three to eight.

- with 3-8 statistically independent criteria, having a maximum score in just 2 criteria suffices to make a person the most popular interaction partner;

- with 9-90 statistically independent criteria, one needs a maximal score in 3 of the criteria to become most popular; and

- with 5 billion statistically independent criteria, the most popular person needs only to have a maximal score on 7 criteria.

$$\begin{array}{c} \\ \text{HR} \\ \text{Sales} \\ \text{Manf.} \\ \text{Mktg.} \\ \text{Eng.} \\ \text{Mgmt.} \end{array} \begin{array}{c} \begin{array}{cccccc} \text{HR} & \text{Sales} & \text{Manf.} & \text{Mktg.} & \text{Eng.} & \text{Mgmt.} \end{array} \\ \left[\begin{array}{cccccc} 6.3 & 4.0 & 1.6 & 2.5 & 1.0 & 10 \\ 1.6 & 6.3 & 1.0 & 2.5 & 4.0 & 10 \\ 1.0 & 2.5 & 6.3 & 1.6 & 10 & 4.0 \\ 4.0 & 6.3 & 1.0 & 10 & 1.6 & 2.5 \\ 2.5 & 1.6 & 10 & 4.0 & 6.3 & 1.0 \\ 1.6 & 10 & 1.0 & 6.3 & 2.5 & 4.0 \end{array} \right] \end{array}$$

Figure 2. Interaction Value Matrix for 6-party Organization with Differentiation=10

We subjectively judged that 2/3 and 2/6 were sufficiently representative of the whole range. We leave the complete mapping of the diversity dimension to others with more powerful numeric solvers.

What effect does diversity have on knowledge transfer effectiveness? People who receive a larger number of interaction requests will have a harder time responding to those requests under assumptions of "bounded rationality" (March and Simon, 1958). Someone whose favorite interaction partner is one of these "popular" individuals would find it more effective to amend his behavior to account for this type of possible failure. It is precisely this competition for popular individuals that makes the time allocation exercise into a non-cooperative game. This justifies our election to focus on cases where there are three to six criteria. Additional independent criteria reduce the popularity of the most popular individual, thus their scarcity, and hence the need for a controlling structure to ensure optimal distribution.

3.1.2. *Differentiation*

Once people have established their rankings, we need to determine the differences in interaction values between higher-ranked and lower-ranked interaction partners. *Differentiation* is defined as the ratio of the value of interacting with the favorite versus the value of interacting with the least favorite. This particular definition makes it possible to ignore the effect of organization size on the results of the model. Because we are dealing with an idealization and not with a real organization, we take the liberty of assuming homogeneity along two dimensions. First, we assume that each step down the list of rankings reduces value by the same ratio. This means that the sorted list of values is a geometric progression. Second, we assume that differentiation is a homogeneous property of the organization, so all people have the same differentiation ratio. This means that all the rows in the value matrix are permutations of the same list of values. The ranking matrix in

Figure 1 thus becomes at a matrix of interaction values, as shown in Figure 2, for a differentiation level of 10.

3.1.3. *Interdependence*

Huberman and Hogg (1995) introduced "hint production rate" as the average amount of time that must elapse between successive interactions with the same partner in order for that partner to have gathered enough insight to be of help again. In the context of an organization, additional factors influence the ideal time between successive interactions with the same organization member. Different work tasks need to be completed by different members of the team in order to prepare the way for a specific information exchange to be of value to the organization. In Interaction Value Analysis (IVA), we aggregate the effects of those different factors and idealize the requirement into a simple average rate of interaction. The same mathematics used by Huberman and Hogg (1995) to describe a "Community of Practice" can thus be applied to describe the number of interactions one must have with other individuals before a repeated interaction with the same person can be useful. We interpret this rate in IVA as the degree of task interdependence. When there are many interdependencies in the work, then more attention must be paid to related tasks before any specific interaction can once again yield value. Conversely, when most tasks are not dependent on many others, it becomes possible to focus on the same task, and therefore interact with the same partner, at a higher rate.

The nature of organized work is such that a single interaction partner alone does not add value. This is contrasted to an economic exchange model where goods have intrinsic value and free exchange unfettered by a command structure is the only road to the highest aggregate utility.

To normalize interdependence for organization size, we express it as the fraction of the population that must be interacted with between successive interactions with a specific person (Nasrallah and Levitt, 2000).

3.1.4. *Load and Urgency*

Even when people seek interactions with a collection of partners to achieve their goals, popular individuals still become targets of more requests for interaction than they can handle. In other words, the most useful people in the organization will have a queue for their attention, which reduces their overall usefulness as a source. How does this translate to reduced effectiveness? We use a simple representation originally operationalized in an organizational context by Levitt et al. (1999), and inspired by (Galbraith, 1977) and (Mintzberg, 1973). A person who attempts to communicate with a busy potential partner, is simply assumed to give up the attempt after a certain threshold wait period. Failure is defined as a request timing out, or being superseded before a response is generated. We used ideas from (Barrer, 1957) to construct a mathematical model of this concept. A request arrives in a person's in-tray, and depending on how busy the person is, the request may get processed while the requester still needs it, or it may stay in the in-tray until it is no longer required. Since we assume many independent factors may lead to a request being generated, being superseded, or being successfully responded to, we can assume exponentially distributed inter-event times for each of these three types of events, which leads us to a memory-less system. We also assume the busy person will act in a fair manner and respond to requests on a first-come, first-served basis. With these assumptions, the only variables that affect success rate are the ratios between the rates of asking for vs. giving help. The new dimensionless parameters thus introduced are:

- Load = Expected number of requests per person per average response time.
- Urgency = Expected number of time-outs per person per average response time.

We use the term "Load" to represent the ratio of service rate over time-equivalent arrival rate. This represents how much work an organization has relative to its resources. The concept is familiar from standard queuing theory, where the service ratio ρ is used. Since we have several queues in the model, the ρ for each interaction partner is obtained by multiplying the sum of that player's column in the time allocation matrix by the organization's load parameter (defined as a fixed quantity per requester). When someone has 2 as the column sum, for example, then that person is getting the equivalent of two full-time people's requests.

Urgency represents how quickly people demand responses to their requests. It is not the same as load, although growth in a company's transaction volume will tend to affect both. For example, a recently funded Internet start-up might have low load and high urgency, because the funding attracts a large number of employees and other resources, but the rush to ship product and grab market share makes it necessary to speed up all decisions. If the money comes close to running out, load becomes high, too, because management is reluctant to hire more people to keep up with workload. After the company starts trading publicly and things are more stable, urgency will be lower but load will remain high because scrutiny of public investors may cause management to delay hiring more people until they can be sure it is cost-effective to do so.

The mathematical aspects of urgency and load are described in Appendix A.

3.2. Optimum vs. sub-optimum

It is relatively straightforward to find one's optimum allocation of time among interaction partners when the only constraint on how often one can go to one's favorite is derived from interdependence. This is the "inessential" game model, where the success of one player only depends on the frequency of that player's interactions. The formula is:

$$\text{success rate for interactions from a to b} = \frac{1}{1 + (\text{size} \times \text{interdependence} \times (\text{time allocated by a for b}))} \tag{1}$$

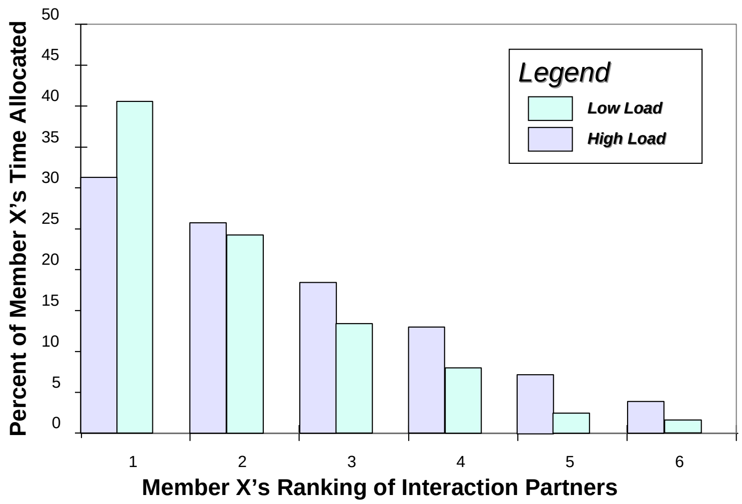
Deviating from the optimal allocation, either up or down, leads to a reduction in individual effectiveness, but has no effect on others' effectiveness. Global effectiveness is reduced by exactly the sum of individuals' reductions.

No management oversight of communication choices is necessary for this inessential case. In real life, low-intensity contacts whose frequency never increases beyond a trivial level (e.g., diffuse communities of practice) do not need a management structure at all.

We illustrate the concept of different optima using figure 3, which depicts the model output for an arbitrarily chosen context. We determine how each participant would best allocate his or her time among interaction partners in a hypothetical six-party organization. (Note: the (Nasrallah and Levitt, 2000) paper showed how the effect of organization size can be eliminated by re-normalizing parameters.) The bars show how a typical member of that organization might optimally allocates his or her time among the six choices.

3.3. Comparison of Optima

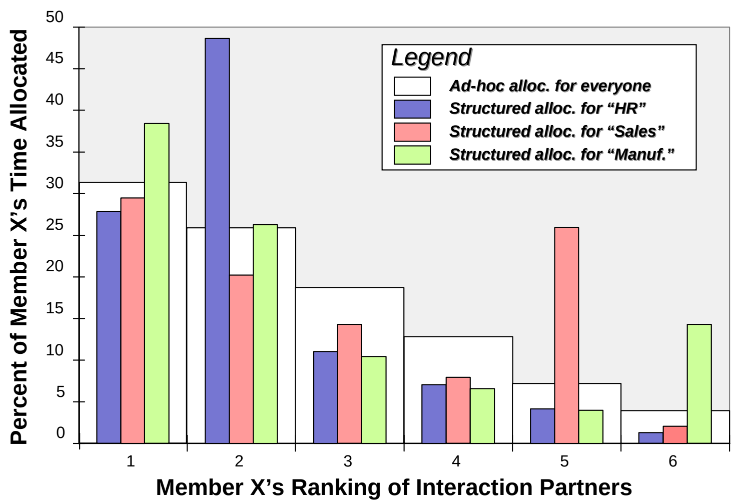
When we consider the effect of resource constraints arbitrated by impatient queuing within the Interaction Value framework, the expression for organizational effectiveness becomes complicated (see Appendix C, equation (14)). After we do all the calculations, we discern a most interesting property. Varying the values of the model parameters described above can now make a unique core appear or disappear. In other words, sometimes the Nash Equilibrium of individual optimal time allocations is identical to the global optimal time allocation, and sometimes it is not.



The vertical axis shows the percent of time spent by the participant whose interaction histogram is being plotted. The numbers on the horizontal axis represent the ranking of others in the organization as potential interaction partners; The favorite interaction partner is labeled as 1 and the least-favored is labeled as 6. The darker bars show an optimum allocation of time for all players in an inessential game which corresponds to infinite capacity. In other words, if everyone has enough free time to render assistance to all requesters, then the best behavior in this particular organization would be to for each player to allocate about 41% of his or her time to his or her favorite interaction partner, and about 2% to the least favorite. When time becomes more of a constraint, then the most popular people in the organization will be tend to become back-logged with multiple incoming requests. Now everyone is better off if all equally reduce the amount of time spent seeking interactions with their respective favorites to 33%. The time saved is then allocated among some of the lower ranked interaction partners. This time allocation is shown by the lighter gray bars.

Figure 3. Sample Time Allocations Among Interaction Partners

We now take a closer look at the difference between these two classes of optimal time allocations. Recall from Figure 3 that the Nash equilibrium time allocation distribution was found to be identical for all participants when plotted against their ranking of interaction partners. Although each participant may have a different favorite, the amount of time spent attempting to interact with one's favorite is identical



The vertical axis shows the percent of time spent by the participant whose interaction histogram is being plotted. The numbers on the horizontal axis represent the ranking of other participants, with one being the favorite interaction partner and 6 being the least-favored. The pale wide bars show an optimum allocation of time for all players in a game where members optimize their own output individually (i.e., locally) in light of all other members' allocations (i.e., in a Nash Equilibrium state). The thinner bars show the (different) time allocations necessary to achieve the greatest global output, which in this example is higher than the output reached under Nash Equilibrium.

Figure 4. Sample Time Allocation demanded for Formal Structure

for all participants under the Nash equilibrium. Figure 3 showed how much of each member's time would be optimally allocated to each of that member's possible interaction partners sorted by rank. The two distributions contrasted in Figure 3 represent two different contexts, e.g., with differing values for the "load" parameter.

Either of the two distributions in Figure 3 may be for a context whose global optimum is identical to the Nash equilibrium of local optima. The same distribution may well be the Nash equilibrium but not the global optimum in a different context. Figure 4 depicts one such context. The wide, pale bars in Figure 4 represent a Nash equilibrium distribution identical to the "high load" distribution in Figure 3.

To achieve the highest possible sum of interaction values, it is necessary to make some non-obvious deviations from the Nash equilibrium behavior. The thin bars of Figure 4. provide a details of one hypothetical set of deviations for three of the participants whose interaction partner rankings and values appear in Figures 1 and 2 respectively. The illustration's numbers were calculated using medium settings for load, slack, and interdependence, and high specialization. The global optimum follows from having the "HR" participant (represented by the first of the three bars in each series) allocate 50% of his time to his second favorite and 27% to his favorite (etc. as shown), and the second person allocates about 28% of her time to each of her favorite and her fifth favorite, and so on. The need to enforce this cooperation requirement is synonymous in IVA with the need for some sort of management structure that channels communication frequencies towards the global optimum.

A review of Figure 1 will reveal the one distinction between the different members of the organization that is allowed for in this globally homogeneous model. The homogeneity assumptions we made mean that all model parameters apply equally to all participants, but different participants are still making choices of favorites independently of one another. What distinguishes the first two members from the third is that the first two both vie for the same favorite (see Figure 2). Hence both have to make greater reductions in their use of that favorite when moving from the Nash equilibrium to the global optimum. Other participants have to make less of an adjustment when making the same transition. Note also that "HR" has a second-favorite who is not anybody's favorite. "HR" can thus do no harm to the organization if he only interacts with that second favorite interaction partner (incidentally himself) 50% of the time as shown in the previous slide. By contrast, "Sales" has to go all the way down to her *fifth* favorite before finding someone who is not anyone's favorite. That fifth favorite, "HR", is the partner with whom "Sales" can spend all the time left over because "Management" is a popular interaction partner and cannot fulfill all "Sales's" requests for face-time. The third player, personifying "Manufacturing", has a favorite, "Engineering", who is not the favorite of anyone else. "Manufacturing" thus gets to allocate its time in a pretty regular diminishing curve until it gets to "HR" again, with whom he must spend more time than with the preferred "Sales", "Marketing" and "Management" partners, because they are relatively more popular and thus less often available.

As a result of all this micro-behavior, a series of trends emerges in the variance between the two optima as plotted against the five parameters. We interpret these trends in the following section.

4. Results

The idealized IVA model we have described so far is elaborated in Appendices A, B and C. It turns out that the optima we need to find can be obtained by ordinary numerical optimization techniques. We performed several numerical optimization runs using the Newton Method with quadratic fitting, as implemented by version 7.0a of Microsoft Excel, ©1985-1996, Microsoft Corporation. We hard-coded two sets of constraints: that proportions of one's time cannot be negative, and that the sum of all those proportions must add up to 1. We used these worksheets to generate charts linking the values of the parameters to the percent difference between the global optimum and the one-by-one (Nash) equilibrium. The percentage difference between the globally optimum aggregate interaction value and the aggregate interaction value at the locally sub- optimal Nash equilibrium represents the maximum value that a management structure can contribute to an organization where knowledge is universal and access is not limited by geography – a "Virtual Corporation" from Davidow (1992), or an "Ad-Hocracy" from Mintzberg (1983). This is our dependent (output) variable, and we denote it by the term "Value of Structure."

We chose four example scenarios to illustrate how one might interpret the model results. These are compared to organization contingency theory predictions for each case and across all cases. Since we have four input parameters against one output variable, we use three-dimensional plots with different pairs of the five input parameters on the x and y axes, and the output on the z axis. For each such plot, the three input parameters that are not shown on the axes are controlled for; i.e., they are set at a fixed value that represents a specific organizational situation. These values are displayed in the top right corner of the graphs.

4.1. Illustration 1: Military under different Loads

The background for this military example was obtained from interviewing a former US Navy officer from the Construction Battalion (the "Seabees"). She explained that the degree of bureaucratic structure inherent in all operations was often much higher than what would have been indicated by common sense. The cost of the bureaucracy was deemed higher than its benefit during normal peacetime construction projects. The rationale for the "Seabees" nevertheless having a high level of structure is that Seabee construction projects will occasionally have to be carried out under battle conditions, which do not obtain most of the time.

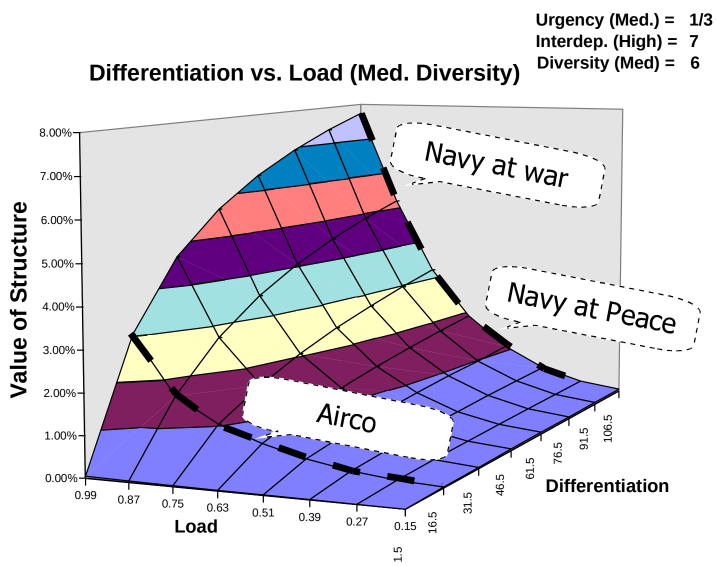


Figure 5. Value of Structure for "Military" Example

To illustrate how the Interaction Value model accounts for this distinction, we plot the value of structure against differentiation and load. High differentiation is what characterizes military organizations, since they mobilize large numbers of individuals who will necessarily have a high variation in skill levels. Time of battle equals high load, as that is where combatants are called upon to respond rapidly to interaction requests, to the limit of their capacity. The upper bold, dashed line in Figure 5 shows how a military organization goes back and forth on the load scale while maintaining the same differentiated mix of individuals. The high end of the curve justifies the need for high communication structure at all times, since it is not possible to fine-tune a response to battle conditions by adding and removing the habits and regulations that constitute communication structure in the military.

Contrast this to "Airco", a commercial airline with mostly college-educated professionals, thus having a lower level of differentiation. The lower bold, dashed line in Figure 5 shows that, since the sensitivity to load is not as high, it is possible to get by with a level of structure that is not too far from the ideal under average load conditions. This is why one is less likely to hear complaints about stifling bureaucracy in an organization such as a commercial airline where differentiation is lower and load is never as high, even in the worst Christmas snowstorm, as in a raging battle to secure a beachhead.

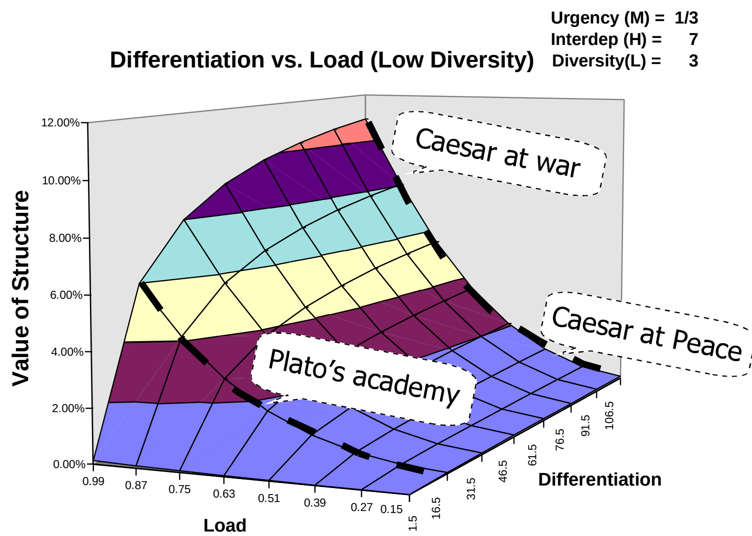
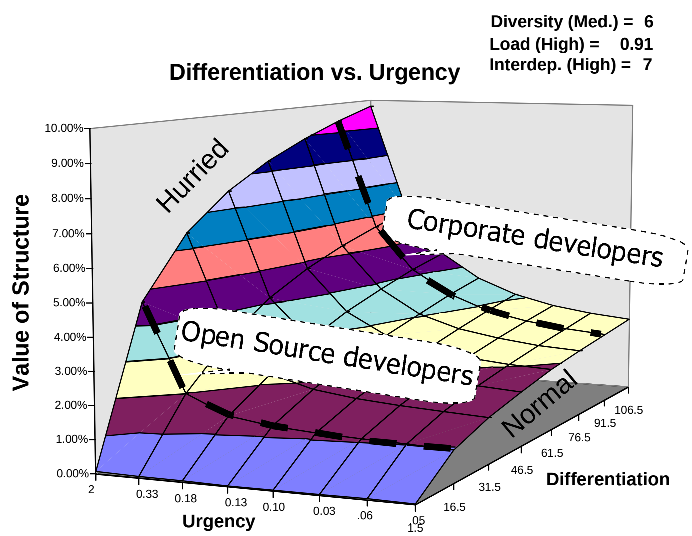


Figure 6. "Ancient Military" Example

Figure 6 shows how the effect of reducing diversity to a value of 3 (independent, equally weighted selection criteria) has no effect on the overall shapes of the curves. The only change is that the value of structure at maximal differentiation and load goes up from 8% to 11% of the organization's productivity. We can relate this to the real-world example of a military organization in historical times. Although the armies of Julius Caesar, for example, were arguably as differentiated in terms of skill level as today's military, there were fewer distinct skill sets available at those times. This meant that a rigid command structure was even more important then than it is now in keeping the organization functioning during the high-load times of war. An organization, like an academy, with less differentiation in the same society (interpreted as the same diversity level), had less need of structure than its military counterpart when faced with taxing work loads. Across societies, we see that the value of structure at high load in the Academy (6 %) is higher than in Airco (3%) because the diversity in ancient times was lower. This is despite the observation that during low load periods, the value of structure may have seemed as low in all instances: the military organization with its high differentiation, the civilian one with its low differentiation, ancient society with its low diversity, and modern society with its high diversity. Structure can add value and thus be cost-effective in all but the modern, civilian organization when the ability to respond to high-load needs is significant to the success of the organization.

4.2. Illustration 2: Open Source Development under different Urgency requirements



Since we are looking at modern-day software development, we set the diversity to medium to reflect the limited but significant number of different types of expertise needed. We use a high interdependence because large software systems will only work if its sub-units are properly coordinated. Finally, we use a fairly high load because we are assuming active projects instead of a possibly more idle average state. The latter case would produce a similar contrast between Open Source and Corporate development, but the value of structure would be lower across the board..

Figure 7. Value of Structure for "Open Source" Example

This example was provided by an interview with developer Sam Ockman (Dibona et al., 1999). His experience with developing operating system software under the Open Source paradigm indicated that he sometimes had to develop certain modules under tight time constraints. These conditions did reduce the effectiveness of the unstructured support network that characterizes the Open Source community.

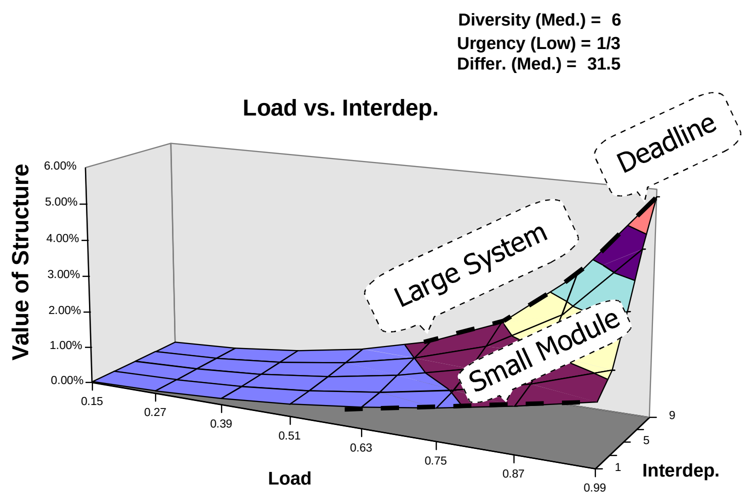
The explanation for this phenomenon is the uniformly high level of competence necessary for participation in Open Source development. This (informal) requirement is so stringent that individuals in the Open Source community will go to great lengths to protect their reputations for competence. The lower bold, dashed line in Figure 7 shows that an impatient individual can still receive good support in less differentiated organizations performing highly interdependent tasks. As long as the average load is not at a maximum, no communication structure is needed to oblige people to share information with specific interaction partners. The value of structure remains almost as low for that impatient individual as it is for people who can afford to wait longer for responses. In contrast, a commercial development environment has less experienced programmers interspersed with experts, so its differentiation level is higher. In that environment, structure becomes valuable when deadlines loom and people cannot wait for answers. This is illustrated by the upper bold, dashed line in Figure 7.

4.3. Illustration 3: Large Software Company for Varying Interdependence

In contrast to Open Source development, the first author's experience in a corporate software development environment led to the following example. We observed that the workload increases close to the code-freeze dates. At those times, management exercised tighter control at the level of the product as a whole, but small teams working on the autonomous modules continued to operate under looser control by their team leaders. The difference between the formality of communication structure at the two scales is explained by variations in interdependence. Figure 8 shows that when interdependence is low, load does not predispose the organization towards tighter structure (lower bold, dashed line). In real life, a programmer working on a small module with tightly defined interfaces is not dependant on other programmers on a day-to-day interactions, and hence can work harder to meet a deadline is without much interference from his manager. When interdependence is higher, e.g. for interactions between user interface and functional design, the graphic designers and product managers in charge of those features need to spend more and more time in meetings with higher management as deadlines approach. This is because structure becomes more valuable as deadlines push the load higher (upper bold, dashed line).

4.4. Illustration 4: Health Care Organization at Varying Diversity

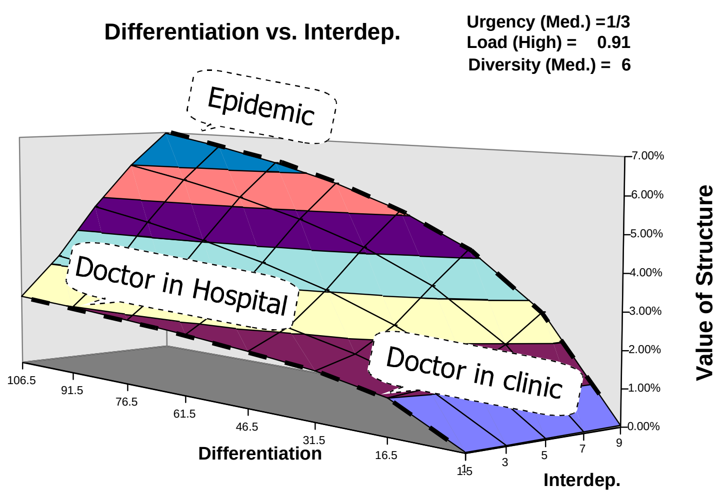
The final illustration in this series comes from accounts in the popular press about the failings of, and resistance by physicians and patients to, health maintenance organizations (HMO's). Attempt to impose a tight



This example examines software development in a corporate environment, so we set differentiation to a medium level to reflect the larger variation in levels of experience in such environments. Diversity is also medium (as in all the other modern-day examples) because the work is in one field but the field contains many sub-disciplines. Urgency is low because large software developers are notorious for letting deadlines slip in order to ship a product that does not seriously malfunction.

Figure 8. Value of Structure for "Corporate Software" Example

rein on medical practice leads to many problems. For instance, the San Francisco Chronicle reported in December 1999 that health insurance purchasers derived lower costs from looser cooperatives of individual medical practitioners than from traditional HMO's. We explain this from an Interaction Value perspective by noting that most of the work of doctors treating different patients is not very interdependent. Every patient is different, and differences are primarily addressed locally. The lower bold, dashed line in Figure 9 shows that the value of structure is minimal and usually not worth the cost. This is regardless of whether differentiation is high, as in a hospital with many levels of doctors, interns,nurses and orderlies, or low, as in a clinic with several doctors sharing support staff. Only when interdependence is high **and** differentiation is medium to high does it begin to pay to manage people's interactions. One example of such a case would be teams of volunteers



High load and medium urgency characterize the medical profession. There is usually a high ratio of patients to doctors (or nurses or paramedics). Response times are dictated by the patients' bodies, which have many different types of conditions requiring different response times. These response times average to medium in the model. Diversity is medium again because there are many sub-disciplines in medicine. Differentiation can vary based on the incidence of less skill-intensive disciplines. Interdependence varies according to the patient's medical symptoms and the assorted treatment strategies. Treatment of a skin rash may have low interdependence for the dermatologist while treatment of severe diabetes would have medium interdependence among the patient's specialist doctors, lab technicians, and other care givers. High interdependence is rarely observed in a medical context, with the possible exception the outbreak of a contagious and unknown disease where the symptoms and past behavior of several patients are compared by all their doctors to find the source or treatment of the epidemic.

Figure 9. Value of Structure for "Health Care" Example

assisting in controlling an epidemic, as shown by the upper bold, dashed line in Figure 9.

4.5. General Observations

We can generalize from the examples above and the requirements in 2.1, to say that structure adds value to organizations when:

– Load is high and

– Diversity is low to medium, and

– Interdependence is medium to high, and

– Differentiation is medium to high, and

– Urgency is medium to high

Diversity is the parameter that represents the complexity of environments. More complexity means more criteria for ranking interaction partners, hence less of a chance of bottlenecks and less value from regulating interactions. Differentiation correlates inversely to the pervasiveness of uniformly trained individuals. A high degree of professionalization makes the differentiation parameter low (because the distinction between the highest and the lowest is less). Low differentiation lowers the value of structured communication vis-à-vis ad-hoc organization. High load combined with high urgency corresponds loosely to a hostile environment; more both favor management structure. Urgency influences overall effectiveness in the same direction as high load (March and Simon, 1958). but it does not favor structure as much as load does. This explains why fast-moving companies in the high-tech area tend to place no value on restrictive management structures. Information in the high-tech world becomes outdated much more quickly than in the traditional company. High-tech companies are thus inherently unable to use communication structure to improve information exchange efficiency, unlike more traditional companies that suffer more from load than from urgency.

5. Conclusions

Our results compare well with published qualitative research in organization contingency theory (see page 3 for exact citations), as illustrated in the table I above. Interaction Value Analysis (IVA) thus emerges as a sound theoretical framework, with greater explanatory power than previously published rules of thumb for organizations. IVA allows us to model and analyze the interplay among a set of variables that affect the value of structured communication in organizations. We have demonstrated the model's potential by obtaining general predictions about specific industry situations. Those situations were described using specific, objectively measurable parameters which were treated as homogeneous across the population of an idealized organization. This

Table I. Comparison of Contingency Theory Recommendations and IVA Predictions

Mintzberg, Burton & Obel	**Interaction Value Analysis (IVA)**
Technically complex projects require more coordination.	Higher load & interdependence imputes a higher value to structure.
Groups of experts require less management intervention.	Low differentiation (skill variance) imputes a lower value to structure.
Threatening conditions demand more structure.	High load & urgency imputes a higher value to structure.
Complex environments are best handled by an ad-hoc organization	Large number of skill sets (diversity) imputes a lower value to structure.

is only the beginning. With additional calibration and validation, Interaction Value Analysis may help to further investigate, articulate and elaborate current knowledge about the theory of organizations.

On the practical level, the simple and abstract approach taken in this paper will, after suitable calibration, allow future practitioners to begin to give advice about organization structure to companies, or whole industries. For example, an Interaction Value analysis study can determine the degree of diversification and differentiation most appropriate for a company expanding into a new market, or, depending on the levels of task interdependence, differentiation, diversity, load and urgency , a firm can determine how much guidance to provide for coordinating work in a specific type of project. And so on.

The results of the homogeneous models encourage us to seek more knowledge about specific organizations that we can observe and represent more precisely by relaxing the homogeneity assumption. Since the model can be solved/optimized numerically, it should also be possible to make the values of the five parameters heterogeneous between different parts of the same organization. For example, firms can give more resources to important departments. They may value the effectiveness of some parts of the organization more highly than others. Interdependence may also differ between different parts of the organization. As long as the number of variables does not become too large, the partitioned or tiered versions should still be tractable and therefore amenable to numeric solution.

6. Next Steps

We propose two paths of future research. One seeks out observations of real situations where observed interaction patterns seem to approximate those that the model recommends for a given context. The other seeks further optimizations of the pure mathematical model under less restrictive assumptions about participant attributes and behavior.

6.1. Field Research

The Interaction Value Analysis paradigm can serve to guide field research. For example, a researcher might look for the values of parameters like differentiation, interdependence, diversity, load and urgency in real companies. It is essential for the success of future research to find out, for example, the degree to which assuming total homogeneity of these values throughout the organization skews model results. Parameters are clearly often different for each project or department in a company. We need to know how to aggregate, or average, diverse observed values of the same parameter in the same organization. The results of an idealized, homogeneous model would not be meaningful or relevant without this. Such data collection and aggregation methods are the key to calibrating the Interaction Value model.

More generally, by imposing bounded-attention constraints on the Huberman and Hogg (1995) model, the modeling framework presented here can be used to pose several interesting questions. For example, we might seek to:

- find the best mix of generalists and specialists in the organization;
- gauge the cost of nagging "bad apples" who use up the time of expert sources who might be of more use to other advice seekers;
- investigate the ramifications of alternative criteria (e.g., random, tit-for-tat, expectation of future reciprocity) for selecting which seeker to help first when a source has a queue of requests in his or her in-box;
- impute underlying preferences or competence distributions from the observation of interaction frequencies within a social network of researchers;
- predict and attempt to control the extent of clique formation in different situations;
- place upper and lower bounds on the value of trust between members of an organization; or
- investigate the effects of skill level and/or cultural differences among employeed of a company proposing to perform similar work in different parts of the world.

6.2. Mathematical Research

The second type of research involves refining the mathematical representation. The current assumptions are simple enough that it would be feasible, though tedious, to obtain closed-form expressions for the shapes of the curves. We could also investigate the effects of more fundamental changes in the assumptions. For example, the way in which people choose whom to help might not be based on first-in, first-out. The pattern of request generation and fulfillment might not be completely random as we assumed.

It would be interesting to do further game-theoretic analysis of different combinations of favorites in order to determine how a player's power varies with his pattern of favorites. Power would be defined as value a player can add to any coalition according to Shapley (1953).

We also observed some empirical properties in the investigation that other researchers might prove mathematically. For example, we observed that the attention distribution curves plotted against the ranking of the interaction partner at Nash equilibrium were identical for all participants.(See figure 3). This observation begs for a simple mathematical explanation. The corresponding curve at the global optimum was not as simple. It would be valuable to know what assumptions about utility curves for business interactions would give a similar divergence between the Nash equilibrium and the global optimum for attention allocation. This divergence came about because we diverged from the requirements for a competitive equilibrium as defined by Debreu (1959). Will this divergence increase in magnitude as we construct different models with slightly different assumptions? For example, what would happen to the two optima under reciprocal selection, i.e., when people respond more readily to requests from those with whom they may wish to interact themselves, or with whom they have successfully interacted in the past? Answers to such questions will be of interest not only to students of organization theory, but also to economists and mathematicians.

Appendix

A. Probability of communication request failing (due to waiting too long in queue)

For the purposes of this model, we assume that communication requests are generated as a Poisson process with single rate λ that applies to all individuals generating requests. Requests directed at a single individual are processed on a first-come-first-served basis, by a single server that operates as a Poisson process with rate μ. Following (Barrer, 1957), we also allow items in the queue to "time out" before being served. This is variously known as the impatience, defection, or survival phenomenon. In Interaction Value Analysis, it represents a communication that is no longer necessary for the work at hand. The time each request spends in the queue before defecting is also treated as exponentially distributed with rate ζ. This is in contrast to Barrer and subsequent studies, where time spent before defection is a constant. In the treatment below, we make the additional assumption that defection can occur during service. Organizationally, this represents, for example, a memo being answered after the sender has already received the desired information elsewhere: the communication is still treated as a failure, and the respondent is allowed to move on to the next request. Mathematically, this means that an item in service is just as likely to be lost to defection as any other item in the queue.

Definitions: 3 independent rates describing 3 exponential distributions for time between events:

μ = rate at which a communication is processed (service)

λ = rate at which communications arrive

ζ = rate at which a communication becomes useless and leaves the queue (defection)

These rates describe a continuous-time Markov chain (specifically a birth-death process) with states $N = 0, 1, 2, 3 \ldots$. The state of the system at any time t is completely described by the number of requests $n(t)$ in the system (queued or in service.) The birth rate is

$$\Lambda(n) = \lambda \qquad \text{for } n \geq 0$$

The death (departure) rate is

$$M(n) = \mu + n\zeta \qquad \text{for } n \geq 1$$

The expression we wish to obtain is the probability of success, defined as the probability that a request receives a response before it times out. If the queue is empty, then the first arrival's success probability is derived from a race between two Poisson processes:

$$\begin{aligned} P[\text{service before defection}|\text{empty queue}] &= \frac{\text{service rate}}{\text{total departure rate}} \\ &= \frac{\mu}{\mu + \zeta} \end{aligned} \tag{2}$$

When there are several requests in the queue, then the chances of staying in the queue until acquired for service are determined by a series of similar races. A simple way to arrive at a reasonably accurate probability is to use the steady state assumption, i.e., to set birth and death rates as equal.

$$
\begin{aligned}
P[\text{service before defection}] &= \frac{\text{service rate}}{\text{departure rate}} \\
&= \frac{\text{service rate}}{\text{arrival rate}} \\
&= \frac{\mu \sum\limits_{n=1}^{\infty} P_n}{\lambda}
\end{aligned}
\tag{3}
$$

where P_n is the steady state probability of there being n requests in the system. By definition, the sum of all possible P_n is 1. Equation (3) becomes

$$\frac{\mu}{\lambda}(1 - P_0) \tag{4}$$

Now in the steady state, we can derive P_0 by observing that:

$$
\begin{aligned}
P_1 &= P_0 \frac{\lambda}{\mu + \zeta} \\
P_2 &= P_1 \frac{\lambda}{\mu + 2\zeta} = P_0 \frac{\lambda}{\mu + \zeta} \frac{\lambda}{\mu + 2\zeta} \\
&= P_0 \frac{\lambda^2}{(\mu + \zeta)(\mu + 2\zeta)}
\end{aligned}
$$

We simplify the expressions above by introducing the ratios:

$$\rho = \frac{\lambda}{\mu} \tag{5}$$

$$k = \frac{\mu}{\zeta} \tag{6}$$

So

$$P_2 = P_0 \frac{\rho^2}{(1 + \frac{1}{k})(1 + \frac{2}{k})} = P_0 \frac{\rho^2\, k^2\, k!}{(k+2)!}$$

and

$$P_n = P_0 \frac{\rho^n\, k^n\, k!}{(k+n)!} \tag{7}$$

The above treatment assumes that k is an integer. Since we are dealing with idealized states, we do not lose any information when we only treat cases where the rate of defection is an integer multiple of the rate of service. We call this number the organization's slack, and its inverse is the urgency.

Next, we determine the steady-state value of P_0 in the usual way, by summing all the P_n values to infinity and setting the sum equal to 1.

$$\sum_{n=0}^{\infty} P_n = 1$$

$$\sum_{n=0}^{\infty} P_0 \frac{\rho^n\, k^n\, k!}{(k+n)!} = 1$$

$$\frac{1}{P_0} = \sum_{n=0}^{\infty} \frac{\rho^n\, k^n\, k!}{(k+n)!}$$

$$= \frac{(k!)\, e^{(\rho\, k)}\, G(\rho\, k, k)}{(\rho\, k)^k}$$

$$P_0 = \frac{(\rho\, k)^k}{(k!)\, e^{(\rho\, k)}\, G(\rho\, k, k)} \tag{8}$$

where G is the cumulative gamma distribution, defined as

$$G(\chi, \alpha) = \int_0^{\chi} \frac{x^{(\alpha-1)}\, e^{-x}}{\Gamma(\alpha)} dx \tag{9}$$

*Note that this is an alternative way of expressing the incomplete gamma function $\Gamma(x, a)$. We selected this particular algebraic representation because it was easier to work with during the numeric optimization phase. See (*Fogiel et al., 1980*) or (*Pearson, 1983*, p.636)for details.*

Substituting (8)back into equation (3):

$$P[\text{success}] = \frac{G(\rho\, k, k+1)}{\rho\, G(\rho\, k, k)} \tag{10}$$

In the context of a group of people vying for the time of a single server, we need to adjust the generic ρ by the percentage of time each person devotes to issuing requests to a particular server j. The organization-wide parameter *Load* is the value of ρ when exactly one full-time equivalent issues communication requests. So for any particular pair i, j

$P[i$ succeeds in communicating with $j](\mathit{Load}, k) =$

$$S_{ij}(\mathit{Load}, k) = \frac{G(\mathit{Load} \times k \times \sum_{i=1}^{n} p_{ij}, k+1)}{\mathit{Load} \times k \times \left(\sum_{i=1}^{n} p_{ij},\ G(\mathit{Load} \times \sum_{i=1}^{n} p_{ij}, k) \right)} \tag{11}$$

We note that, because of people leaving queue due to time-outs, the queuing system remains stable even if arrival rate exceeds service rate. The more relevant rate for stability is the rate at which people leave the system **either** through being served or through timing out. Of course, although the queue is stable, the failure rate becomes very high when the time-out rate approaches the service rate. This is reflected in the results section above.

B. Probability of communication failing to add value (due to workflow)

When we introduce queuing failure to the model, we find that the percentage of time spent trying to interact with someone is no longer uniquely determined by the percentage of time spent actually interacting. This makes it more difficult to accurately represent the effects of interdependence. We choose to work with the same expression from (Nasrallah et al., 1998), namely

$$P[\text{Communication adds value}] = Z_{ij} = \frac{1}{1 + p_{ij} \times Interdep} \tag{12}$$

Recall that *Interdep* is the ratio of two rates, one for communications with a particular partner and one for communications in general. Higher interdependence means that more work had to be transacted via communications with others before a successive communication with a particular partner can have any value; low interdependence means that repeated communications with any particular partner can yield value (i.e., be successful) with fewer outside communications being necessary. In the context of communication attempts failing due to queuing too long, using the ratio of communication attempt rates (i.e. the general rate to the specific rate) models time elapsed between attempts, not useful work performed between successful communications. This is because success rates vary widely between interaction partners, so more communication attempts no longer necessarily imply more communication successes. It becomes very complicated to gauge the relative productivity of both parties of the communication, since each may have a very different set of interaction partners and thus very different success rates.

We did experiment with an alternative formulation, where

$$Z_{ij} = \frac{1}{1 + Interdep \times \frac{p_{ij} \times S_{ij}}{\sum_{i=1}^{n} p_{ij} \times S_{ij}}} \tag{13}$$

This formulation takes into account the communication seeker's rate of failure due to queuing in determining whether the workflow failure occurred. In other words, instead of optimizing individual I's total wait time between communications with individual j, it considers time spent successfully communicating with others vs. time spent successfully communicating with individual j. The practical offshoot was that the distinction between structured organizations and unstructured organizations became much smaller. Of course, real-life dynamics are more complex than either formulation above. The time taken for conditions conducive to a certain knowledge transfer to be of value depends on the success rates of both sides of each communication, and also on the success rates of those persons' other communication partners. We therefore decided to stick with the simplest expression because it would have had the highest weight in any linear combination of such expressions.

C. Aggregate Probability of Communication Success

The final expression for the aggregate knowledge transfer effectiveness being maximized under both types of constraints is thus the simple multiplication:

$$\begin{aligned}\text{Effectiveness} &= \sum_{i=1,j=1}^{n} p_{ij}\, h_{ij}\, S_{ij} Z_{ij} \\ &= \sum_{i=1,j=1}^{n} p_{ij}\, \frac{n - \text{ranking of } j \text{by } I}{n-1} \\ &\quad \times \frac{G(Load \times k \times \sum_{i=1}^{n} p_{ij}, k+1)}{Load \times k \times \sum_{i=1}^{n} p_{ij},\, G(Load \times \sum_{i=1}^{n} p_{ij}, k)} \\ &\quad \times \frac{1}{1 + p_{ij} \times Interdep}\end{aligned} \tag{14}$$

This expression was what we numerically maximized by varying p_{ij} for various combinations of the parameter values ($Load$, k, $Interdep$, $Diff$).

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