Advances Towards a

Societal-Scale Decision-Support System

Marko Antonio Rodriguez
Computer Science Department
U.C. Santa Cruz – 2004
okram@soe.ucsc.edu

For John Galt

ABSTRACT

Collective intelligence has been defined as the ability of a group to provide more effective solutions to problems than could be otherwise provided by any of its individual members working alone. Social-structures are the means by which humans are able to synergistically combine their efforts to provide high-quality solutions to the problems facing the group. Over time, these structures have grown in scale and complexity to encompass political institutions that span vast landscapes of heterogeneous individuals to militaristic forms capable of orchestrating effective large-scale behavioral feats. With computer and network technologies, the potential for more advanced societal-scale information-processing systems is now possible such that a general-purpose societal-scale decision-support system may begin to be envisioned. Unlike typical group decision-support research, a societal-scale system is faced with both a heterogeneous user population and problem-space. In designing such a system it is important to understand how the 'collective's mind' is modeled via a shared mental map of the group and how the 'collective's mindset' is maintained over fluctuating participation levels of its constituent members. Methods in both problem-space partitioning and group preference modeling are presented within a theoretical and design framework to further the potential development of a societal-scale decision-support system capable of providing synergistically derived solutions to any representable problem. In concert, all of these ideas provide the foundation for the implementation of societal-scale decision-making system in a real-world context.

1 INTRODUCTION

The area of human-collective problem-solving, from the vantage point of computer science, has been studied primarily in the research agenda of group decision-support systems. Work previous to this moment has focused primarily on computer support systems for small groups in a particular problem-domain (Fjermestad & Hiltz, 1997). It is only recently that research efforts have begun to move away from small-group decision-support systems to societal-scale decision-support systems (Turoff, et al. 2002). In these efforts, large-scale decision-support system development has come to realize necessary research efforts revolving around fluctuating group participation (Rodriguez & Steinbock 2004), problem modeling (Heylighen 1988), decision-making for natural-language problems (Turoff, et al. 2002), and general computer-mediated collaboration techniques (Nikos, et al. 1999; Smith 1995). This thesis presents two theoretical advances focusing on *maintaining the collective's perspective during times of lossy participation* and *problem-space modeling in computer-mediated collaborative workspaces*. Together these two ideas provide advances in the area of societal-scale decision-support systems.

Dynamically Distributed Democracy, DDD, is a social network and accompanying energy distribution algorithm that provides a representative structure to an organization such that competent individuals—as seen through the eyes of the group—have a higher degree of influence in domain-specific problem-solving processes. This algorithm is demonstrated through simulation to have benefits in scalability because the ability for it to accurately represent the group is mainly a function of the connectivity of the network and less of the participation of its members (Rodriguez & Steinbock 2004). DDD provides the mechanism by which any active subset of the population is weighted appropriately such that this subset is a holographic model[1] of the group as a whole. This idea has impact in large-scale decision-support system research where representing the group's perspective over fluctuating participation levels across heterogeneous problem-domains is of utmost importance—ensuring civil stability through an accurate model of the collective's will.

Organizational Domains, OD, are the second novel concept provided by this thesis. Organizational domains provide another layer of complexity to the DDD paradigm supporting a means by which the group

[1] Holographic modeling is related to holographic images where any portion of the image is a lower-resolution representation of the whole image. Group holography refers to representing the behavior of the whole within a subset of the whole.

can organize its problem-space into manageable problem-domain subsets. This, in turn, not only allows problem classification, but also allows individuals to partition their understanding of one another's competence in problem-domain categories thus further refining the group's self-reflective model. An algorithm is then presented which allows an individual to determine the collective's realizations of their area of expertise—their domain of maximum energy potential. This algorithm has benefits in societal-scale decision-support research where task distribution and influence in decision-making processes are determined by domain specific attributes of the individuals participating in the group.

The first part to this work provides a theoretical problem-solving system framework and demonstrates how the ideas aforementioned are applied. This framework is then further refined into a general design specification to provide the reader a practical understanding of how such a system would be built and deployed in a real-world environment. The final section of the thesis discusses how a system implementation would be evaluated in a real-world context. In concert, all of these ideas provide the foundation for a societal-scale information-processing environment capable of harnessing the collective potential of the group to solve any representable problems.

1.1 Foundations for Human-Collective Problem-Solving

This section provides the foundation for understanding collective-intelligence and presents some novel concepts that support the realization of a societal-scale human-collective decision-support system. These theoretical ideas will play a major role in understanding how DDD and OD can be implemented in a real world system.

1.1.1 The Environment and the Collective Realization

The 'objective' *environment* shared by a collective of individuals has no inherent property that supports the realization of a 'problem' separate from the internal workings of the group cognition. Therefore, to any subset of the collective, a *problem* is a perceived portion of reality that under the proper transformation could potentially provide a greater utility than presently realized (Heylighen 1988, 1990). From the discipline of cybernetics, it has been argued that the environment is constructed based upon the perceived needs of the individual (Gaines 1995; Heylighen 2000). This idea is supported up to the collective in that the group shares a common understanding of the external environment in so much that the members share the same perceptual mechanisms (physical perceptors as well as internal models such as language and culture) and in so doing are able to come to a realization of a *collective-subjective environment*. Without a shared environmental realization, the notion of a problem would only be an internal concept represented within the modeling framework of the individual's cognitive faculties. If a problem is to be solved in a collective fashion, there must exist a model of that problem, within a shared medium of the group, by which that problem can be communicated amongst members of the group (Hutchins 1995; Heylighen 1999). Therefore, a *problem-model* is a formal representation, within a shared-medium, of a low-utility aspect of the collective's environment. Individuals then review the problem-model in order to formalize a *solution-model* that satisfies the problem-model's constraints—irrespective of any rippling deleterious effects it may incur on other aspects of the environment. Finally, the *solution* will be defined as the perceptible environmental outcome of the implementation of the formalized solution-model. This lays the foundation for a canonical understanding of how an environment is perceived to have problems that need to be solved via some problem-solving mechanism.

1.1.2 Problem/Solution-Space and the Collective Workspace

As individuals within the group interact with their environment, they go through the process of problem modeling. The collection of all problem-models within the group can be called the group's *problem-space*. It is within this space that these problem-models are transformed into their respective solution-models to be stored within the group's *solution-space*. The formalized solution-models, within the solution-space, are then implemented as the collectively agreed upon course of action. The problem-space and solution-space representations can be seen as the collective-workspace by which these humans represent and share their ideas about the world (Hutchins 1995; Twidale et al., 1997). Again, without this collective medium, problem-solving would exist solely within the modeling framework of an individual's cognitive faculties and would not benefit from a collective effort (Heylighen 1988). It is through this shared medium that the cognitive resources of the collective can synergistically coexist to formulate solutions that are greater than what could possibly be achieved by any individual working alone. All italicized ideas mentioned above are represented below [*Figure 1*].

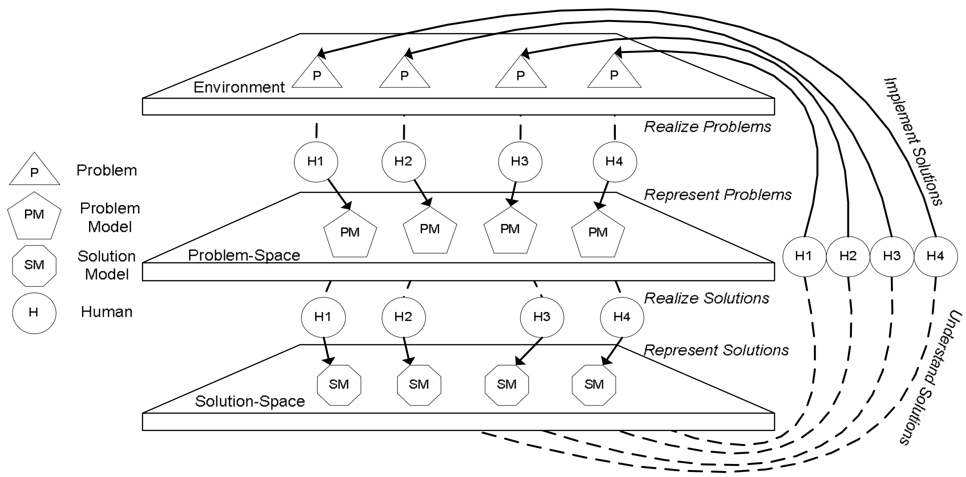


Figure 1: A Canonical Model of a Collective Problem-Solving Process

It is important to note that in the collective problem-solving effort outlined in *Figure 1*, there exists no collaboration among individuals. This simplistic model does not take advantage of the collective's ability to synergistically provide higher-quality solutions, but instead takes advantage of the group synergistic ability to generate a higher throughput of solutions since environmental problems are solved in a parallel effort. Representing collaborative problem-solving would only complicate a preliminary grasp of these concepts.

1.1.3 Problem-Modeling and Decision-Making

In the canonical model presented in *Figure 1*, each individual within the group is capable of formulating a problem-model without collaboration with other group members. In a real-world scenario, this becomes increasingly difficult as the complexity of the problems begin to grow larger than what an individual's mental framework can model. In such cases, problem-modeling may only require one individual to make an initial shallow realization of the problem, but through a more in-depth analysis, spanning various domains, a collaborative effort of domain specialists would be required to create an accurate collective model of the problem. The act of formulating a problem is called *problem-modeling*.

Representing a problem is an important step in problem-solving since a good representation can make a hard problem trivial, and a bad representation make a trivial problem hard (Heylighen 1999, Russel & Norvig 1995). For this reason, a selection process must occur in which problem models are judged, by the group, according to their potential at providing a low-energy effort in the solution-modeling process. The *decision-making process* is a selection process since it doesn't generate new problem-models but instead selects high-quality models. As demonstrated in *Figure 2*, the problem-modeling stage generally sees a growth in the number of problem-models and through the decision-making stage this model pool is pruned down to the most optimal model as seen by the group. Together problem-modeling and decision-making is the *problem-generation process*.

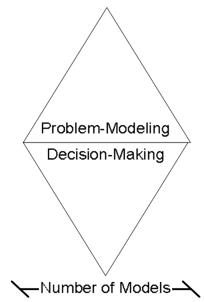


Figure 2: Size of Problem-Model Pool over the Problem-Generation Process

1.1.4 Solution-Modeling and Decision-Making

Once a problem has been modeled within the problem-space, the collective can begin to transform that problem-model into a solution-model ready for implementation in the environment. In order to take advantage of a collaborative effort, two distinct stages must first be traversed. *Solution-modeling* is the process by which individuals review the problem-model, understand the issue at hand, and via the use of their internal cognitive machinery, generate a collection of solution-models that may be of potential use. Hybrid solutions may then be formalized via the act of collaboration. At the end of the solution-modeling process the solution-model pool, like the problem-model pool, must be trimmed via a selection process. In order to yield a single solution-model for the problem, the group must enter a decision-making process in which the group collectively decides, via some *voting algorithm*, which solution-model should be implemented. This two-stage model is coined here as the *solution-generation process*.

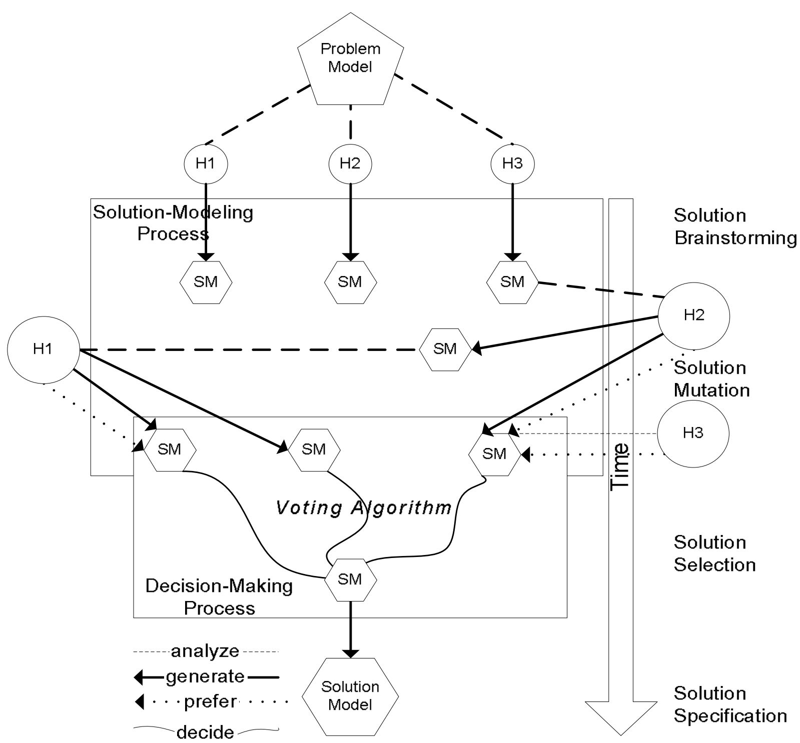


Figure 3: Solution-Generation Process Model

The above example demonstrates how a problem-model is transformed into a solution-model via the solution-generation process. It is important to note that this same principle applies to the way in which a perceived environmental problem is transformed into a problem-model. In *Figure 3*, there are three human participants actively involved in solution-generation. At first, each individual reviews the problem-model and provides their own unique solution-model based solely on their specific internal realizations. Once these three solutions-models have been represented in the solution-space, the individuals are able to analyze each other's models such that they may generate new and potentially higher quality solution-models. After a certain limit (context dependant), the group enters the decision-making process in which the models in the solution pool are voted on. A voting algorithm (context dependant) is able to aggregate the preferences of the individuals to yield a model that is reflective of the group's perspective.

1.1.5 Voting Algorithms and the Context

The areas of social choice theory and machine learning are full of algorithms by which a collective can aggregate the individual perspectives of its members in order to yield a collective perspective (Alton-Scheidl, et al 1997). Different algorithms are more appropriate than others depending on the context for which they are needed. For example, where a numeric solution is required, simply averaging the views of all the individuals may be sufficient. For more linguistic models, where numeric averaging isn't possible, a Borda-Count or majority vote over various annotations may be the appropriate method. It is up to the problem-modelers and solution-modelers to decide the appropriate voting algorithm used to filter the model pools. This obviously leads to the recursive paradox of voting on how to vote. Therefore, it is up to the system implementers to decide how such algorithms are to be selected given the context of the model.

1.1.6 Problem-Solving as the Unification of all Processes

Problem-solving is the unification of all the modeling and decision-making processes described above. This is the general idea that a collective-subjective environmental problem is modeled in a collaborative effort and then solved via a similar mechanism. Problem-solving also encompasses the act of implementing the collective's solution and thus completing the loop—bringing the group closer to equilibrium with its perceived environment.

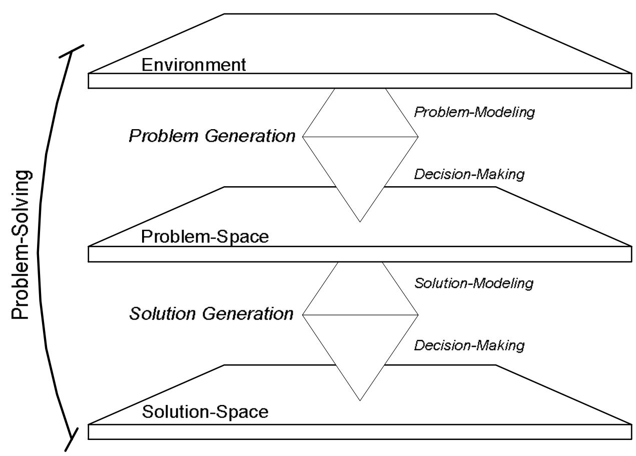


Figure 4: Problem-Solving as the Unification of all Processes

1.1.7 Model-Quality vs. Model-Throughput

During any problem-solving endeavor there exist two main complimentary model attributes that are balanced in accord with the constraints impinged by the context. *Model-quality* can be defined as the effectiveness of the model at providing the next stage of problem-solving a low-energy effort. Where a high-quality problem-model tends to represent a problem so clearly that a solution is easily determined (Heylighen 1988). Likewise, a high-quality solution-model can be seen as one that generates a high-utility outcome or as one that reduces the propagation of ill effects to other areas of the environment. In general, the ability to produce quality solutions is a function of the level of expertise of the group as well as the amount of time they have to problem-solve. Thus the *model-throughput* of the group is constrained by the group's desired level of model-quality. The general principle is that higher-quality models tend to require more time to generate (Steinbock, et al. 2001).

1.2 Group vs. Societal Decision-Support Systems

There has been much literature published in the domain of group decision-support systems. This section provides arguments for why typical group decision-support research differs from societal-scale decision-support research.

1.2.1 Heterogeneity of Individuals and Problems

Group decision-support systems are usually built for a particular problem-solving domain in which the individuals participating in the group decision process are of similar background in terms of the type and level of expertise that they share (Turoff 2002). More advanced, cross-domain systems do exist to support complex problem-solving, but still at this level, the type of expertise is explicit in the system design. The reason for this is that most decision-support systems rely heavily on human interfaces tailored to a particular domain (Nikos, et al. 1999). A general-purpose system wouldn't have this luxury save through domain-specific extensions to a basic implementation. Also, a general-purpose system hopes to tap collective intelligence on a societal-scale. In doing so, the problems realized by the group and the expertise of the group are extremely diverse in topic and depth. Therefore, unlike group decision-support system research, a societal-scale decision-support system would need formalized requirements regarding the ad hoc categorization of the expertise of its individuals and their problems as they are realized by the collective.

The two novel approaches presented by this thesis have an explicit understanding of the diversity in both the problems and the population. The DDD social-network enables the group to create a *bottom-up peer-reflective* understanding of the varying degrees of expertise of each individual over the discourse of problem-domains. Furthermore, these domains are generated over time—from a preliminary 'tabula rasa' representation—as individuals come to categorize the nature of their perceived problems. It is only through the union of each individual's categories that a collective realization of the problem space can be understood. Therefore, unlike the top-down development of group decision-support system, the societal decision-support system makes no explicit claim to the type of problems that will face the group, nor to the type of members that will compose the group. This information, in this problem-solving engine, is formulated via a self-organizing bottom-up methodology as individuals interact with each other and with the environment at large.

1.2.2 Fluctuating Participation and the Collective Perspective

The *collective perspective*, as defined by this thesis, is the realized course of action by the group in the case that every member participated in the problem-solving process. As members abstain from participation, the ability for the group to maintain that perspective defines how well the collective's self-model is able to handle fluctuating participation levels. With division of labor and parallel decision-making, dealing with fluctuating participation levels is of utmost importance. The idea of the collective perspective, as seen in this thesis, makes no rational claim as to the most accurate voting algorithm. The ideas presented lie directly beneath this abstraction and therefore the voting optimizations are left to the research of social choice and economic theorists. The idea of the collective perspective is made more explicit in opinion-based decision-making such as seen in value-based political polling. When all individuals actively vote on their opinion, the final decision, provided by the voting algorithm determines the collective's will. If the group maintains a model for holographically representing itself then as members refrain from voting, the same opinion poll would yield (essentially) the same outcome as the full participation vote. The ability for a group to represent itself over a subset of its population determines the ability by which that group is able to represent the collective perspective over varying degrees of participation.

In typical group decision-support system research, the collective perspective is upheld via a requirement of the participation of all members in all decision processes. In these systems, fluctuating participation can have dramatic effects on the solution quality of the group (Steinbock, et al. 2002). As the participation level of the group dwindles, the amount of solution-models generated decreases. This may not be so ominous if the remaining individuals are experts generating high-quality solutions. However, when decision-making is required, the voice of non-expert individuals may outnumber the experts and the group may choose non-optimal solution models. Therefore, full group participation in small groups is realized via asynchronous support mechanisms. In such scenarios, decision-making usually happens on a time limit in which group members make their choice within a time window, thus ensuring a higher potential for full participation while not requiring simultaneous participation (Fjemestad & Hiltz, 1997).

In a societal-scale system, the ability for the full group to participate in all decision processes is impractical and potentially impossible. In light of this, the collective perspective must be represented without explicit reference to the aggregation of each member's decision. The social network algorithm presented in this thesis provides a holographic model of the group's perspective via a representative power structure that modulates over varying degrees of participation. Unlike standard representative structures where decision-makers are expected to participate, this model makes no explicit reference to a representative, in so much that representatives are those individuals who are participating and have a decision-strength greater than their own individual power.

2 DECISION-SUPPORT SYSTEM ARCHITECTURE

The architecture of a simplified example system is now presented before moving onto the detailed discussion of the algorithms that support this structure. The purpose of this simplified system is to provide the reader with a concrete framework in which to relate the theoretical models and a real-world scenario. The system described is basic in design and therefore does not embody the full potential of what a fully-fledged system could provide (both in usability and functionality), nor does this high-level design address all of the issues a real system would need to confront, such as security, distribution, load management, and fault tolerance.

This basic system is composed of two main functional components. One component, called the *collective workspace component*, comprises the shared medium by which individuals are able to represent their problem-models and solution-models. The second component, called the *decision-support social network component*, performs the power distribution computation to bias the relative influence of various individuals within the collective workspace.

2.1 Collective Workspace Component

Problem representations are stored within the problem-space according to their domain specific categorization (*Figure 5-Left*). Since group decision-support system research has focused mainly on domain-specific implementations, a general-purpose design must provide the user a method by which they can categorize their problems. This idea not only provides a means by which models can be categorized, but also plays a major part in understanding how a heterogeneous population can be organized according to their respective areas of expertise.

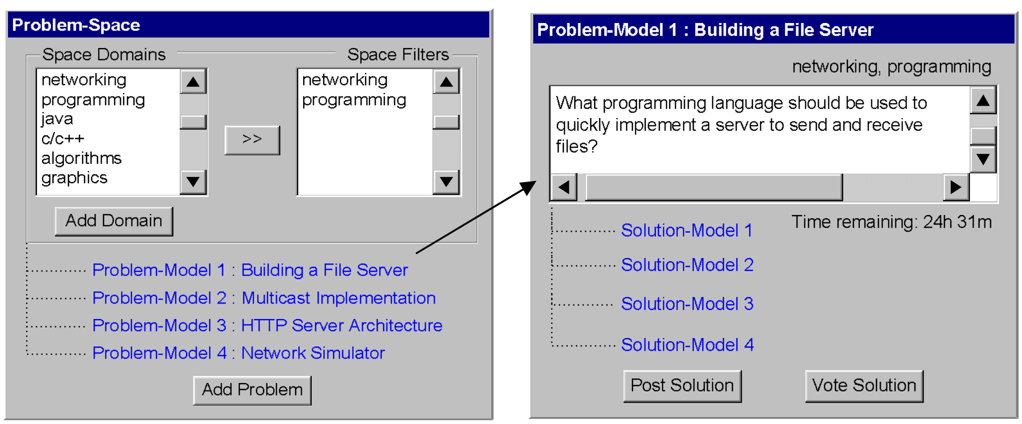


Figure 5: Problem-Space Representation (Left) and Problem-Model Representation (Right)

In this simple system, individuals are able to create linguistic models of their problems such that other individuals, competent in the problem-domain, are able to provide the appropriate solution-models (*Figure 5-Right*). As individuals interact with a particular domain of the problem-space, they are able to select problems that they believe they may be competent enough to provide solutions to. In such a case, individuals are able to see which solutions have been provided by other users as a means of backing solutions they feel are correct or, in the case that no satisfactory solution-model exists, they may provide a model of their own making.

Voting on a particular solution-model to a problem-model is the way by which the decision-making process proceeds such that the solution-pool of a problem-model is pruned to the one optimal solution-model as seen by the group. Time constraints may be imposed to provide a deadline by which individuals are able to provide solution-models as well as decide which solution-model they feel is most appropriate given the problem-model. In order to bias the relative influence of individuals within the decision-making process, a decision-support social network component can be used within this system.

2.2 Decision-Support Social Network Component

The decision-support social network component provides the power structure that regulates a user's involvement in the collective workspace. The purpose of this network is to provide a ranking system by which solution and problem-models can be organized. When model pools need to be pruned, lower ranking models can be removed. When a model must be chosen, high ranking models can be selected. This network can also be used by an individual to get the groups perspective on their level of their expertise within a particular problem domain relative to others within the group.

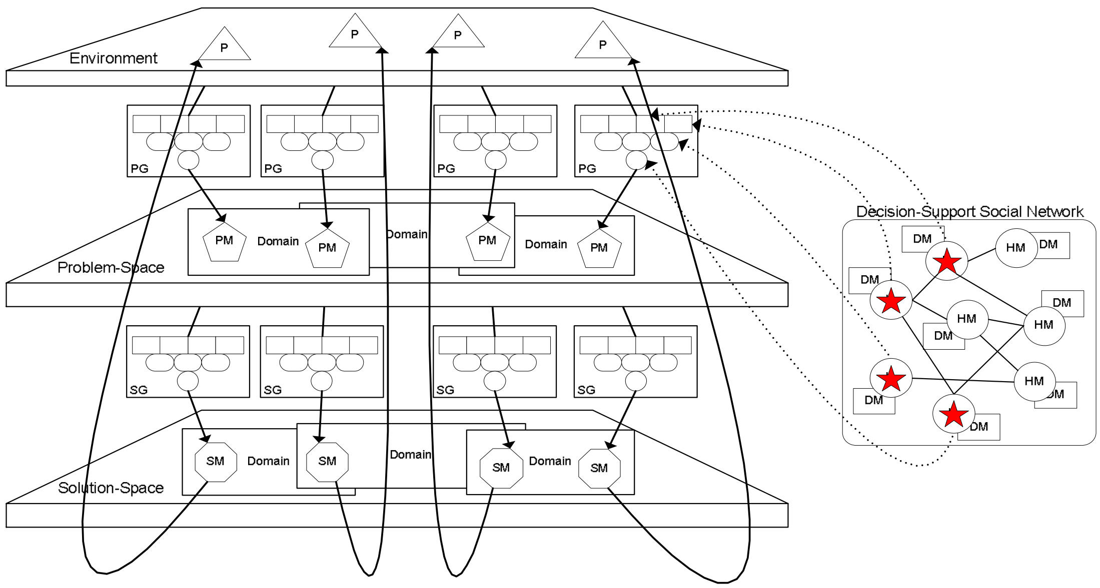


Figure 6: The collective workspace component and its processes regulated by the social network

In *Figure 6*, the problem-generation (PG) and the solution-generation (SG) processes are both regulated by the decision-support social network. This allows individual models to have a visibility in the collective workspace as well as determining the relative decision strength of individuals as they vote on models during decision-making processes. The following section describes the algorithmic process governing the decision-support social network.

3 DYNAMICALLY DISTRIBUTED DEMOCRACY

DDD serves two main functional purposes within a societal-scale decision-support system. First, *DDD is a domain specific power dissemination algorithm that allows individuals to explicitly represent the relative competence of one another over all domains of inquiry*. Any individual may actively participate in any problem-solving process, but it is only through the aggregation of power from non-participating individuals that they acquire relative weight within the process. The meaning and effect of this power is left to implementation specifics but on preliminary insight, power in decision-making can be thought of as vote strength while power in collaborative modeling can be seen as the visibility of one's models to the group. Secondly, DDD is *an algorithm by which individuals can realize their domain specific power such that they can better assess their relative contribution and potential function within the system.* Individuals are constantly peer-reviewed so that as their abilities in one domain wanes, they may find their participation better suited in another. Therefore, an individual's area of expertise is made explicit through the dynamic energy distribution within the DDD network.

Before describing the DDD algorithm, a framework is presented for understanding how DDD fits within other structures of power currently expressed in large-scale decision-making systems. The idea of *representation* is the canonical model for understanding what it means to have power in a system. The more representative an individual is of the societal will, the more individuals they are able to model and thus the idea of *social compression* will be discussed. The collective perspective is maintained over role specification, parallel decision-making, and lossy participation via the use of representation. When an individual is participating in a problem-solving effort with a subset of the population, determining the relative representative power of that individual is important in understanding how much influence that individual should have in that domain. This power distribution over any subset of the group represents the collective's holographic self-reflective model.

3.1 Models of Power and Degrees of Representation

When organizations are faced with decisions to make, it becomes impractical for all members of the institution to have an active participatory say in each problem-solving process. The reason for this is twofold. Firstly, the *overload problem* is encountered when an organization does not have the proper information-processing infrastructure to handle the large-scale inundation of the models and decisions of all its members. Secondly, the *expert problem* states that in a heterogeneous population, not all members of the institution are capable of providing useful contributions to the problem-solving effort in all domains. Therefore, the full participation of all members may only incur deleterious noise in the problem-solving process. These two issues, separately and together, have been the driving factors that have caused human organizations to adopt representational power structures as a means of isolating those individuals who are competent in particular domains as being representatives of a subset of the collective. In adopting such a system, the group is balancing the potential for high-quality solutions via a larger solution pool to choose from and at expediting the decision-making process by limiting the amount of processing required to generate the solution output.

3.1.1 Representation as a Social Compression Technique

Utilizing a representative power structure is a technique that a collective can use to compress its perspective over a smaller set of representing individuals. The benefits of this is that the group is able to limit the amount of information processing required to solve problems since decision-making can happen over a smaller subset of the population—thus combating the overload problem. On the other hand, like most compression techniques, as the compression ratio increases between those that are being represented to those representing, the ability of the representatives to capture the perspective of their constituents becomes increasingly difficult.

3.1.2 Degrees of Representation as the Universal Model

Any form of decision-making contains a form of representation. In purely totalitarian systems, there exists one individual who is the representative of the entire group. In such cases, the degree by which the collective perspective is upheld is limited since only one individual is modeling the group's intentions and therefore a totalitarian power structure is a gross lossy compression of the whole. Nevertheless, such a form of power is considered the extreme of a *one-to-many representative structure*. At the other extreme, lies the case where each individual equally participates in the group problem-solving process. This is seen in direct democratic institutions where everyone has an equal participatory say in all matters concerning the institutions evolution. Such institutions model the collective perspective perfectly since there exists no compression of perspective into representative individuals. Such a model is a *one-to-one representative structure*. In between these two models lie varying degrees of representation which, given the context of the problem, differ as to ensure the constraints of the problem are met—solution-quality vs. solution-throughput.

3.1.3 Free-Degree Representation as the Universal Framework

A *free-degree representation framework* is a representational infrastructure that allows a system to dynamically modulate its power structure according to the constraints of the environment—problem constraints, participation fluctuations. Therefore as problem-solving efforts are parallelized and individual participation ebbs and flows, a free-degree system automatically adjusts to account for the context of the problem-solving process in order to uphold the collective-perspective over those actively participating members. The idea is that there is no inherent power structure in a system until a problem-solving effort is initiated. *Only through participation are individuals able to influence the system and only through non-participation are they able to influence the relative power of those participating individuals*. The dynamics of representation is based solely on the activity of the individuals in the problem-solving process.

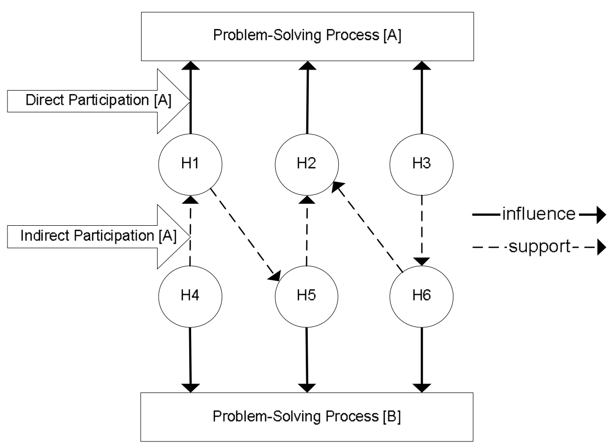


Figure 7: Free-degree of Representation in a Decision-Making Process

According *Figure 7*, suppose there exists a decision-support system composed of six individuals and, at the present moment in time, two parallel problem-solving efforts. If the environment were such that both problem-solving efforts were required to produce a solution at the same time then the collective would have to diverge its focus in order to accommodate the constraint. For this reason, imagine that three individuals (H1, H2, H3) proceeded to participate in problem-solving process A (PSP-A). While, similarly, the other three individuals (H4, H5, H6) actively participated in problem-solving process B (PSP-B). Because of representation, in PSP-A, H2 has the most influence in the process relative to H1 and H3 (via support links). This demonstrates that H5 and H6 are able to indirectly represent their perspective in the PSP-A through the use of representation and thus both processes are able to maintain, albeit of lower-resolution, the collective perspective.

A free-degree structure is one that explicitly models the support links between different individuals such that once an individual is unable to participate in a particular problem-solving process, their influence is propagated to a representative of their perspective. This is dubbed a free-degree model since only given a particular context will the degrees of representation be made explicit. Therefore the resolution of representation is a real-time variable dependant on the participation of individuals—the context.

3.1.4 Static vs. Dynamic Representative Models

An important area of research in societal-scale decision-making systems is handling the issue of fluctuating participation levels (Turoff et. al, 2002). In systems that demand that there be an explicit set of static representatives, these representatives must constantly participate in all decision-making processes if the perspective of their constituents is to be represented. When a system encounters fluctuating participation from its members, a more dynamic representative system may be used where individuals that actively participate are representatives of those that do no actively participate. In this sense, representatives are dynamic based upon the activity levels of the population as a whole.

3.2 Examples of Degrees of Representation

The sections that follow provide examples of the varying degrees of representation in a quantitative form. These examples of groups of four individuals lay the foundation for understanding how DDD, a free-degree representational structure, serves as the optimal structure for collective problem-solving systems since it is able to encapsulate all degrees of representation in a context-sensitive manner. Through the use of these examples and later through the 100-member group simulation we see how DDD is able to maintain the collective perspective at low levels of participation and how the connectivity of the DDD network can remain relatively low thus giving it an argument for a real-world scenario.

3.2.1 The General Representative Model

The general representative model is concerned with presenting a model by which the degrees of representation perspective can be studied in a quantitative manner. This model provides the necessary framework for doing large-scale simulations in order to understand the relative benefits of the varying degrees of representation. For the sake of clarity, the idea of representation will be articulated within the idea of power in decision-making as opposed to power in modeling, since decision-making is generally more familiar to most readers.

Imagine that there is a collection of individuals comprising a group. Each individual has a unique opinion concerning a figurative problem. These opinions can vary over the rational numbers between 0.0 and 1.0. To put this into a real world context, one could imagine that an opinion of 0.0 refers to a strict republican viewpoint while an opinion of 1.0 could refer to a strong democrat and where the ranges between are the hybrid perspectives of the more general population. Next, imagine that each human can either be considered actively participating in the group decision-process or not. A more advanced model that incorporates fractional activity is not examined in this thesis but is outlined in a related publication (Steinbock & Rodriguez 2004). In the diagrams that follow, active participation is represented as a star inside the circle representing the individual. Finally, decision aggregation algorithm is the averaging of the opinions of all those actively participating in the decision-process and therefore takes on a value between 0.0 and 1.0. From here each representative model discussed below will add the appropriate amount of complexity to this generic framework to demonstrate a simulation of real world group decision processes.

Before going onto large-scale simulations involving a group size of 100 members, a small group of four members is demonstrated with diagrams to help explain the ideas surrounding the various representational models. The results of large-scale simulations will prove more provocative than the contrived examples presented next.

3.2.2 Zero-Degree Representative Decision Model

In classic direct-democratic decision-making, the decisions generated by the group are based solely on the opinions of those individuals that actively participate in the decision process. In terms of the resolution of representation, the representation of the group is a one-to-one mapping for every individual. When mapped to a social network, the network contains no representative edges and therefore is a zero-degree decision-making network. In the days of Athens as the mecca of democracy, anyone concerned with group behavior could meet in a large town square to actively voice his opinion. A mediator announced issues and the outcome were deduced based on the loudness of the group over the presented options. This model adds nothing to the general model described above. A certain portion of individuals are selected to participate in the group decision and those that do not, do not have an effect on the outcome of the decision. What is apparent is that as member participation decreases, the group decision becomes less of a reflection of the desired will of the whole—the collective perspective.

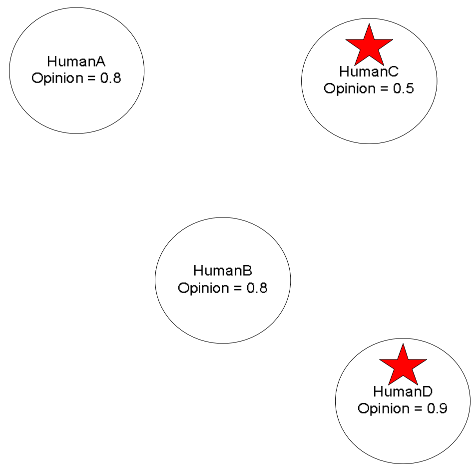


Figure 8: Zero-Degree Representative Decision Model

As an example, assume there is a small group composed of four individuals, each with a generic representation of their opinion type. If only 50% of the individuals are able to actively participate in the decision process the decision is determined by creating a mean average of only those active members' opinions. In the equations below, the set *A* is the set of all active members in the decision process while the set N is the set of all members both inactive and active in the group.

$$Z_{ero}D_{egree}D_{ecision} = \frac{1}{|A|}\sum_{i=1}^{|A|}(\, opinion_i \,) \tag{1}$$

For this particular example, where a star represents active members, the group decision would be the mean of a 0.9 opinion and a 0.5 opinion yielding a group decision of 0.7. The error induced by this model is calculated by determining the difference between the generated decision and the decision determined by full group participation since full participation would yield a group decision that models the groups will perfectly—a perfect representation of the collective perspective.

$$P_{erfect}D_{ecision} = \frac{1}{|N|}\sum_{i=1}^{|N|}(opinion_i) \tag{2}$$

The perfect decision yields a group decision of 0.75. Therefore, the error induced by the zero-degree decision model in this particular example yields an error of 0.05 as determined by the decision error equation below—where the calculated decision is the value determined by *Equation 1*.

$$DecisionError = \left| PerfectDecision - CalculatedDecision \right| \qquad (3)$$

A zero-degree network provides the mechanism by which a perfect group vote could be achieved in the case where 100% of the population was able to participate in every decision process, but in societal-scale decision-making, this is generally not the case. With many decisions varying over many domains, each individual neither has the time to participate in every decision, nor do they have the expertise in every domain to express an intelligent perspective. It is for this reason that a zero-degree network offers little benefit to large-scale problem-solving efforts.

3.2.3 One-Degree Representative Decision Model

Large institutions, troubled by the overload problem, usually provide mechanisms to allow its members to choose a representative of their opinion. Using representative decision-making overcomes the communication issue of aggregating the perspectives of all participating individuals and allows non-expert individuals to have expert individuals speak on their behalf.

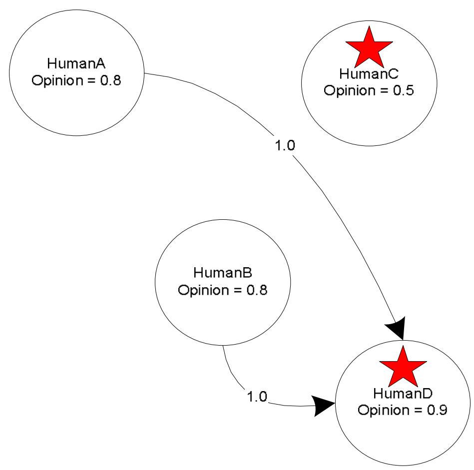


Figure 9: One-Degree Representative Decision Model

Using the same group as presented in *Figure 8 Figure 9* demonstrates how a representative is able to aggregate more power based on the number of individuals he represents. Therefore, adding to the generic framework is the concept of energy, weight, or power, in the representative's opinion. Non-representative humans choose representatives that are closest to their opinion. This is why both *HumanA* and *HumanB* have picked *HumanD* as their representative since they only have a 0.1 difference of opinion with *HumanD* while with *HumanC* there is 0.3 difference.

$$OneDegreeDecision = \frac{1}{|N|}\sum_{i=1}^{|A|}(\,opinion_i * energy_i\,) \quad (4)$$

The calculated group decision, in this example, is a 0.8 and therefore has a decision error of 0.05. A one-degree network allows a group to model its entire population, but as the proportion of non-representatives to representatives increases the modeling ability of the group decreases. Furthermore, two ramifications associated with static representation structures are noticed. First, *HumanA* and *HumanB* are statically non-active participants and therefore static representative structures are only able to utilize the indirect abilities of these individuals to choose representatives—reducing the potential for quality solutions. Secondly, individuals in these structures select one representative of their perspective while a distribution over many representatives may be a better model of that individual's perspective. Together these issues make static one-degree structures unrealistic for a societal-scale problem-solving.

3.2.4 Dynamically Distributed Democracy Decision Model

Dynamically distributed democracy, or DDD, in its most simplistic form, is expressed as a free-degree social network structure and accompanying power distribution algorithm (Rodriguez & Steinbock 2004; Steinbock & Rodriguez 2004). For the sake of simplicity, this example form assumes the group is operating within a single problem-domain. Organizational domain models and their effect on the network only complicate an immediate understanding of DDD and therefore will be addressed in the second half of this thesis. What DDD adds to the generic representational framework is the concept of a weighted distribution of representation. Individuals are able to select multiple representatives of their perspective and distribute their decision power to these representatives based on a difference of opinion that each discovered representative has relative to them. A discovered representative is different from the standard notion of a representative in the sense that there is no explicit understanding of a hierarchy (and its explicit roles) in this model of decision-making—*individuals do not choose amongst a pre-determined set of representatives*. Individuals, through their experiences with the group, are able to identify others that, time and time again, represent their opinions or subjectively express a superior level of competence. The group structure self-organizes as members interact with each other and the problem-domain. Therefore the model of the individual is the shared mental model created by all the members of the group. Member representation is not self-reference, but peer-reference.

node	Human that distributes or aggregates energy particles
activation	Whether or not that human is participating in the decision-making process
edges	Directed edges leaving a node represent that nodes representative preference model
value	The probability that an energy particle will propagate over that edge
energy	The social force that a node possesses and may distribute to its preferred representatives

Table 1: DDD social network terms and definitions

In a particular problem-domain the nodes of the graph represent the individuals that constitute the group. The edges represent the weighted preference that each individual has regarding the belief that the human node receiving the incoming edge represents their opinion in regards to this particular problem-domain. In the extreme scenario, all individuals of the group may actively participate in every decision process, but as members deem themselves incompetent with regards to the nature of the domain or for any other reason, find themselves unable to actively participate in the current matters of the particular domain, these inactive human nodes propagate their energy to other nodes that they have deemed fit enough to represent them. Energy traverses the network until it reaches an active node, wherein at that point, the particle's journey is complete. In the other extreme, where all members, save one individual, deem themselves unable to participate for whatever reason, a decision-making dictatorship evolves. Through the single variable of activity over a set of individuals, DDD is a free-degree representational structure.

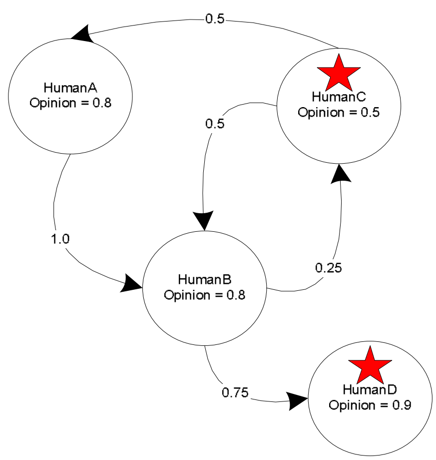


Figure 10: DDD as a Free-degree Representative Decision Model

In the example provided in *Figure 10*, the same four-member group is seen again; only this time each node maintains a preference model of their randomly discovered members of the group—a *preference model* is defined as the set of outgoing edges from an individual. Each edge is given a preference value based on the difference of opinion between the two nodes. These values are then normalized to 1.0 in order to generate an energy particle dissemination probability distribution over the edges.

$$EdgeValue(n_i, n_j) = 1 - |\, opinion_i - opinion_j \,| \quad (5)$$

Unlike the static one-degree representative model presented previous, representation is not a strict relationship between an inactive node and an active node. Instead, an inactive node's energy particles are able to move to other inactive nodes as well as to other active nodes in a probabilistic manner such that each node is able to distribute it's decision power across an array of different active nodes. More figuratively, when an inactive node passes its energy to another inactive node, such as seen from *HumanA* to *HumanB*, *HumanA* is not supporting the decisions of *HumanB* since *HumanB* is not actively participating, but instead *HumanA* is supporting *HumanB*'s preference model. Therefore a representative can be an active decision-maker or an individual seen as having a desirable preference model. The decision algorithm is the same as the opinion aggregation algorithm of the previous one-degree model.

$$DDD_{ecision} = \frac{1}{|N|} \sum_{\mathrm{i=1}}^{|\mathrm{A}|} (\, energy_i * opinion_i \,) \quad (6)$$

When a group decision is needed, the nodes either disseminate energy particles (inactive nodes) or sink collected energy particles into their opinion (active nodes). The preference model of a node is only useful when a node is inactive and serves no functional purpose for active nodes. Therefore, in the above example, the preference model of *HumanC* (the directed edges going to *HumanA* and *HumanB*) does not serve a purpose in this particular computation of the group decision, but may do so in a future decision if *HumanC* becomes inactive for any reason. *HumanA* is an inactive node whose preference model has a 100% probability of passing its decision energy to inactive *HumanB*. *HumanB* then passes both its originally assigned energy and the energy collected from *HumanA* to *HumanC* and *HumanD* according to the probability of their respective preference edge. *HumanC* and *HumanD*, being active participants in the decision, collect the energy given to them and use that energy to amplify the strength of their opinion.

When this group utilizes DDD during its group decision process, during an equivalent 50% participation level, DDD dampens the effects of a limited participation and incurs a 0.0 decision-error, which is a group decision of 0.75. The distribution of energy over the active members of the group represents the relative power that those active individuals have in determining the outcome of the decision at hand. The energy distribution algorithm provides a runtime mechanism by which active individuals of a group are selected as context-dependant representatives of the inactive members. The more energy an active member has at a particular point in time, the more representative that individual is of the group such that energy patterns over the active member subset represents a self-reflective model of the collective perspective with respect to all members of the group (Rodriguez & Steinbock 2004). DDD only articulates which actively participating members of the group are more preferred by the whole. In short, DDD is a framework by which a collection of inactive, non-participating, individuals has an indirect effect in the problem-solving process via their power distribution over the active, representative, members of the group. This distribution is the holographic model.

3.2.4.1 Rationale for Statistical Particle Algorithm

DDD is a specific instantiation of the more general confluence network architecture and associated conflux particle distribution algorithm used for modeling of dynamical systems (Steinbock & Rodriguez 2004). If an energy particle were to bifurcate and take every possible path as it traversed the network, the energy value would quickly lose its numerical precision due to long path lengths and cyclic graphs. Since rounding would occur in such cases, the relative energy strengths would yield inaccurate group models. Instead paths provide a probabilistic value governing the energy particle's route. The distribution of energy over the active nodes is a statistical measure of the networks energy. With enough particles, this probabilistic method provides a statistically accurate measure of what an infinite-precision bifurcation algorithm would provide.

3.2.5 Comparison of Representative Models of Simple Example

The results of the simple four-member different degrees of representation examples are presented below.

Representative Model	Model Decision	Model Decision Error
Zero-Degree Decision Model	0.7	0.05
One-Degree Decision Model	0.8	0.05
Free-Degree Decision Model	0.75	0.00

Table 2: Results of the Small-Group Examples

3.3 Quantitative Analysis of the Representative Models

The four-member group example provided in the previous section demonstrates a simple example outlining the key features of the DDD process relative to other representative models. Interestingly enough, DDD group modeling performance is a function of the connectivity of the inactive individuals and less of a function of the size of the active population. Furthermore optimal group modeling comes at a network connectivity of approximately three. This means that every individual in the population need only know three individuals, active or inactive, to provide DDD the correct amount of information to produce an optimal collective perspective model. This section illustrates these findings to a greater degree in the non-trivial simulation of a group containing 100 members.

3.3.1 Simulation Implementation and Experimental Design Summary

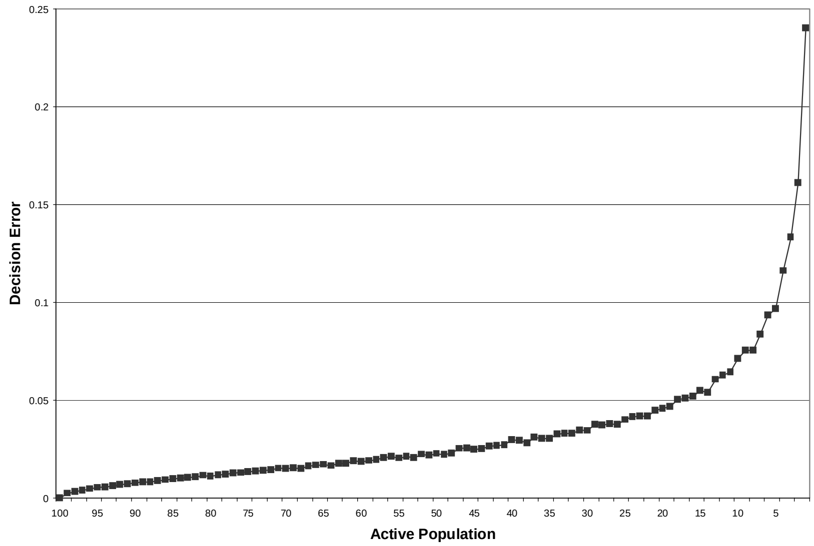
A software simulator was developed to perform parameter sweeps over the various degrees of representation models presented previously. A population of 100 agents with an equal distribution of randomly generated opinion values was created for each model. For direct-democracy simulations, no edges were provided between the individuals of the group such that no power distribution in the form of representation could occur. If a member was active then their opinion was considered, if not, then their opinion was not. For higher-degree representative systems, a population subset was selected to be representatives of the group. In one-degree models, non-representative members had a 100% probability of giving their power to a single representative that was closest in opinion to their own. The directed edge connection could only go from non-representatives to representatives. The group decision is then determined as the average weighted opinion of all the representatives. Finally for DDD, edge density provided the means by which the power graph could be scaled to test how network degree affected the decision error.

3.3.2 Zero-Degree Network and the Error of Non-Participation

3.3.2.1 Hypothesis and Simulation Design

The only variability that exists in zero-degree decision-networks is the number of active participants in the group decision process. Therefore a one-dimensional parameter sweep over the number of active agents was performed to test how zero-degree participation levels affected the group decision error. Through a priori reasoning, it seemed obvious that as the participation level decreased, the amount of error would increase. The function governing this relationship was not known.

3.3.2.2 Results and Remarks



Graph 1: The Decision Error Relative to the Participation Level in a Zero-degree Model

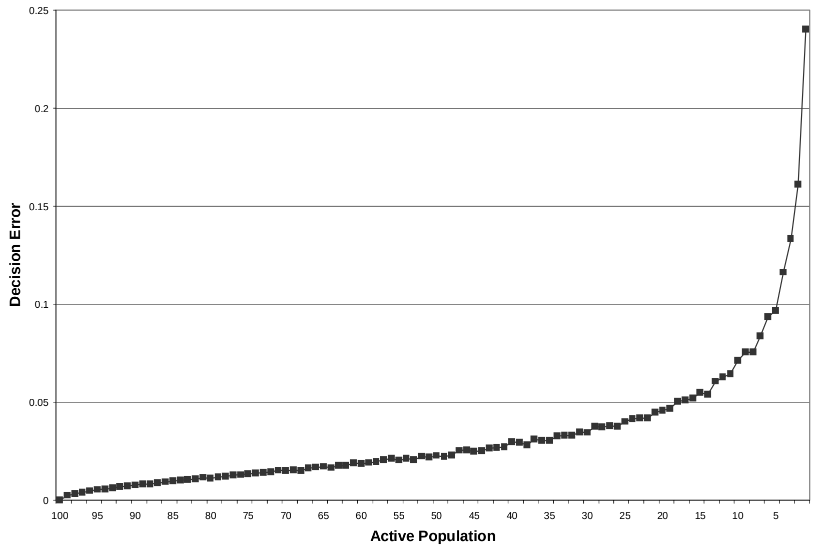
The results of the simulation verified that as the active population decreased from 100 members down to a single individual, the decision error increased. An exponential function governs the rate at which error is incurred. This simulation demonstrates the limitations of using a zero-degree representational network within a societal-scale decision-support system where constant participation in all decision-processes is impractical. As the size of an active population drops, deleterious effects on the collective decision express themselves. This also describes the phenomena of civil unrest in totalitarian systems—systems with one active participant. A single individual is statistically unable to represent the perspective of the collective and thus they incur a high decision-error in their choices.

3.3.3 Representative Democracy and the Clustering Effect

3.3.3.1 Hypothesis and Simulation Design

In this simulation, a random subset of the population is chosen to be active. Inactive members locate an active individual that is closest to their opinion and generate a link to that individual (see *Figure 7*). When a decision is needed the inactive members provide their active constituent their energy value. Each inactive member has a 100 percent probability of disseminating his or her energy to one active member. For this reason, it is believed that as the ratio between inactive to active members increases, the error will increase as well. The function governing this behavior is a priori unknown.

3.3.3.2 Results and Remarks



Graph 2: The Decision Error Relative to the Participation Level in a One-Degree Model

In *Graph 2*, when all 100 hundred members are actively participating in the decision-making process, then there is a 0.0 error. As the degree of representation increases to the point where one individual is representing the whole group, the error increases via an exponential function. This model is in exact accord with the behavior of the zero-degree model. It is interesting to note that even though inactive individuals are disseminating their energy to the closest representative of their opinion, each representative, on average, has an equal say in the decision since from a randomly selected group of individuals, each individual will get an equal amount of energy from the inactive subset. Since each active individual has an equal say, it is equivalent to a zero-degree representation. Therefore, in a heterogeneous population, the probability of equality across potential representatives is equal so as the resolution of the representation decreases so does the error at a rate equal to non-representation.

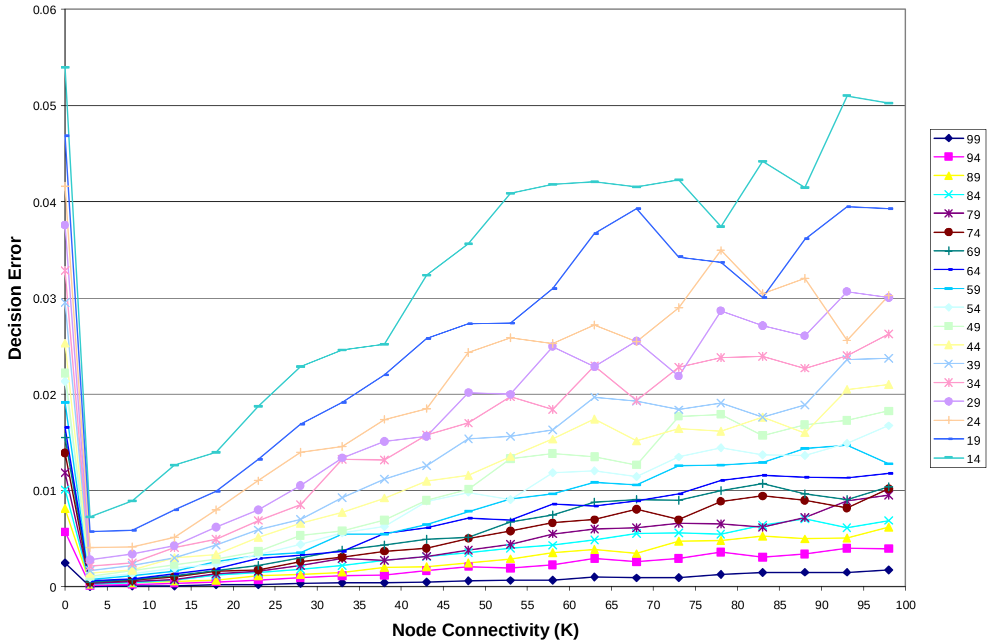
3.3.4 Dynamically Distributed Democracy and the Connectivity Phenomena

3.3.4.1 Hypothesis and Simulation Design

Utilizing the DDD framework allows inactive individuals to propagate their decision-making power to others within the group, but unlike the one-degree model of the previous example, if a representative is inactive, that representative is able to propagate their amassed energy to the individuals they feel are competent decision-makers. Also, since DDD allows individuals to distribute their energy over a range of individuals, it is hypothesized that DDD will weaken the effects of representational clustering by providing a larger representational body to express their opinion.

Active population size and individual preference model size (or node connectivity) are two variables that must be studied to explore how DDD performs when participation levels drop and at what connectivity level will DDD perform the best. It is hypothesized that DDD will suffer an increased decision-error as the population of inactive members increases, but it is believed that as DDD connectivity increases, their will be a linear relationship governing a decrease in the decision-error.

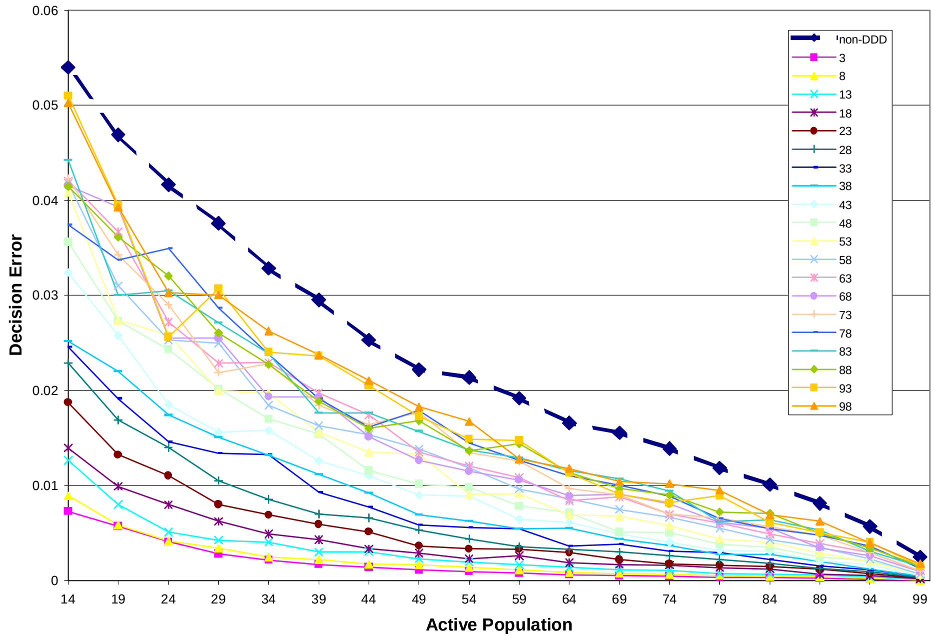
3.3.4.2 Results and Remarks



Graph 3: The Effect of Node Connectivity on Decision Error over a Series of Participation Levels

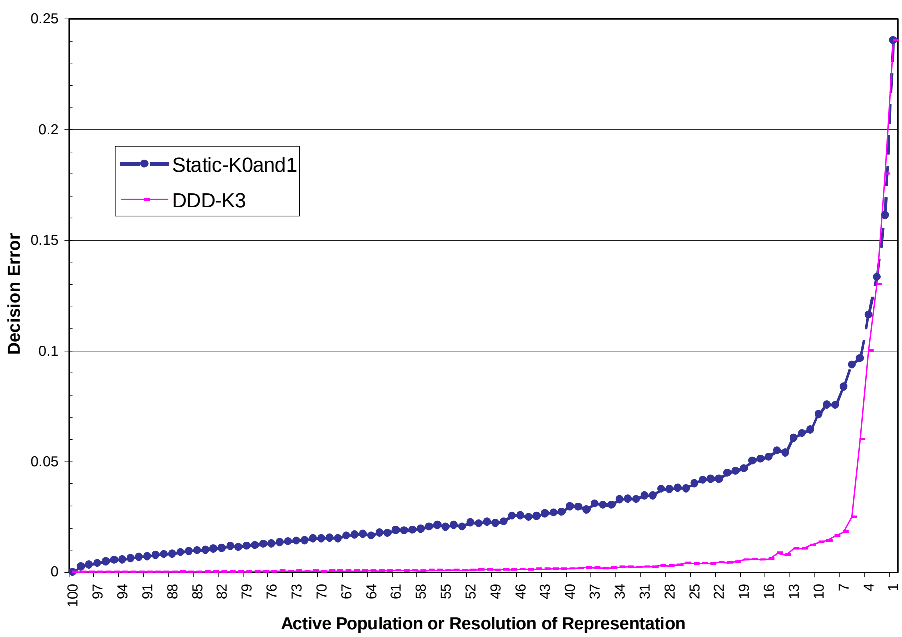
Graph 3 represents a series of activity levels over node connectivity values. What is initially noticed is that, for all activity levels, node connectivity of approximately 3 (K≈3) yields the greatest reduction in decision error. After that, there is steady increase in the error of the network as the connectivity increases. The major impact of this finding is that individuals need only make reference to approximately 3 other individuals in a particular domain for the system to generate an accurate self-reflective model of itself for that domain—OD discusses methods to generalize an individual's preference model over multiple domains. If DDD found its optimal model in a K≈N-1 connectivity then it would seem impractical for implementation since each individual would have to assess the relative abilities of every other individual in the network. This is both taxing on the individual and impractical for large-scale societal implementations. Therefore, *the low-connectivity value discovered provides a strong incentive for the implementation of such a free-degree representational structure in a societal-scale decision-making system.*

An informal mathematical explanation of this low-connectivity can be understood when K=N-1. If an individual were to have a preference model that connected to every other individual in the network the probability values would all approach 0 as the limit of N went to infinity. Therefore for large K values, the probability of a particle taking any edge becomes equal and therefore energy dissemination is random. This mainly explains why as DDD increases its connectivity, the decision error increase—the graph becomes a more random web of interconnectedness.



Graph 4: DDD Connectivity Series over an Active Population compared to the zero-degree network

Graph 4 demonstrations that DDD outperforms both static zero and one-degree power models regardless of the connectivity of the network. In the case that DDD is over connected, annealing algorithms could take hold to prune the network to a lower connectivity value in order to control the accuracy of the network in maintaining the collective-perspective. *Graph 5* demonstrates DDD at K=3 relative to both zero and one-degree power models. Notice the significant dampening of error at low participation levels.



Graph 5: DDD at K=3 relative to the zero-degree and one-degree networks

4 ORGANIZATIONAL-DOMAINS

4.1 Applied Organizational Domains

The DDD framework presented in the previous chapter made no reference to the problem-domain of the participating individuals. For a simple group with a non-diverse problem set, this model suffices. When organizations become more diverse in their decision-making, representing individuals via a single representational structure loses meaning. In the case of such organizations, another layer of complexity can be added to the DDD social network.

4.1.1 Domain Edges

In the example below (*Figure 11*), four individuals are part of a problem solving team for an engineering department. In this engineering department, there exist three disciplines—electrical engineering (EE), computer engineering (CE), and computer science (CS). As the group members interact with each other they come to understand the relative skills of each other regarding these separate domains. For example, *HumanA*, has come to realize that *HumanC* is excellent at solving problems related to electrical engineering. He also feels that *HumanC* is more competent at computer engineering problems than *HumanB*. In order to represent this information in the DDD social network structure, edges are able to carry labeled weights such that when a computer engineering problem is needed and *HumanD* and *HumanB* are the only available active individuals, computer engineering energy flows only over its appropriate preference edge.

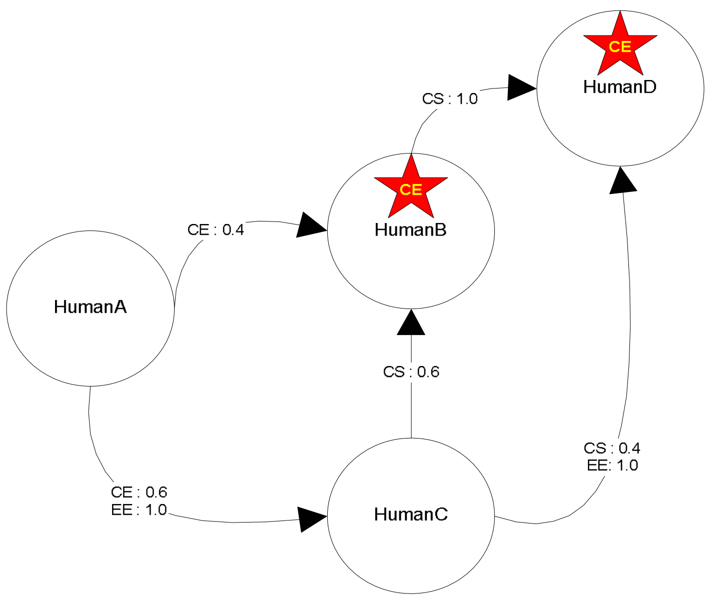


Figure 11: DDD Network with Domain Edges

As can be seen, *HumanB* will amass an energy sum that is 1.4 times as great as *HumanD* since *HumanB* would collect 100% of his own energy and 40% of *HumanA*'s energy in the CE domain. Likewise, *HumanD* would only collect his own energy and nothing else. Even though *HumanA* propagates 60% of his CE energy to *HumanC*, *HumanC* maintains no edge reference governing the propagation of CE. Therefore, in such a scenario, the energy, unable to disseminate, would die.

4.1.2 Fuzzy-Domain Matrices for Cross-Domain Energy Translations

The energy loss potential when using just domain edges within the group power structure can be alleviated to some extent by the addition of individualistic fuzzy-domain models. Fuzzy-domain models are an internal model that each group member maintains regarding the relative similarity between various domains of the group. In simple groups with a relatively small number of problem domains, it is possible for every individual to maintain a preference model for each domain, but as the complexity of the group increases, this becomes impractical. For such societal-scale groups, fuzzy-domain models allow an individual to bypass the explicit preference model and instead provide a relationship matrix describing how a domain specific energy should be behave when it reaches a preference model that doesn't support its propagation. In essence, a domain matrix is a probabilistic filter affecting the probability of the energy particle utilizing another domain's edge to continue its journey to an active node.

	CE	**CS**	**EE**
CE	1.0	0.9	0.7
CS	0.8	1.0	0.2
EE	0.7	0.3	1.0

Figure 12: Fuzzy-Domain Matrix

Each individual, along with a preference model, is also able to maintain a matrix defining their perceived relationship between the different problem-domains of the group. A matrix cell can take on a value between 0.0 and 1.0. The domain matrix in *Figure 12* demonstrates that the individual believes, obviously, that the CE domain is exactly like the CE domain. Furthermore, he also believes the CE domain to be 90% like CS and 70% like EE. For those involved in the engineering discipline, computer engineering and computer science are not all that different because of an overlap in the concepts that they express. Likewise, computer engineering and electrical engineering share an overlap in concepts as well. As can be seen, this individual believes that computer science is only 20% like electrical engineering but fuzzily, electrical is 30% like computer science. These relationships allow an individual to have an atrophied preference model yet still provide the appropriate mechanisms for all domain energy particles to propagate.

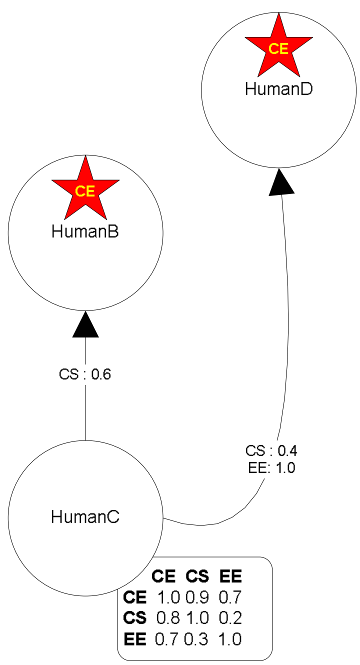


Figure 13: Probabilistic Energy Translation

In the example provided in *Figure 13*, when a CE energy particle reaches *HumanC* it is has no explicit CE domain edge to traverse. Since *HumanC* has made reference to domain edges for CS and EE, the energy particle is able to make a probabilistic 'jump' across one of these edges such that its journey may continue to the active nodes *HumanB* or *HumanD.*

The algorithm that allows energy translations across different domains is as follows:

1. Multiply all domain edge values that have a corresponding relationship to the particle type in the domain matrix by the relationship value.
2. Sum all edges that lead to the same node together to get a new edge value for the particle type domain.
3. Normalize all effected edges to 1.0 to create a probability distribution for that particles traversal.

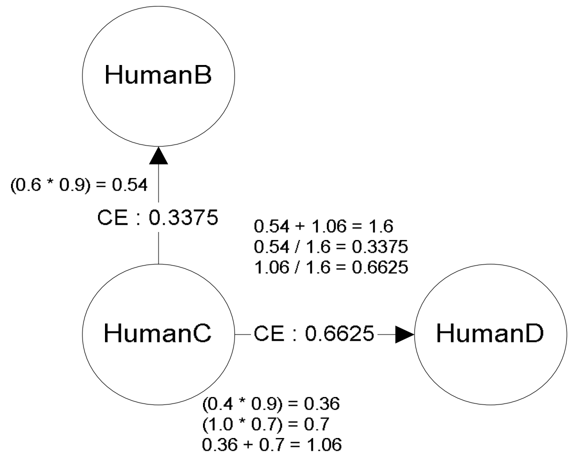


Figure 14: Energy Translation Algorithm

According to the example provide above, multiply the 0.6 and 0.4 edge values for CS by 0.9 since the domain matrix states that CE is 0.9 like CS. This gets new edge values of 0.54 and 0.34 respectively. Next, since CE is 0.7 like EE, multiply the 1.0 domain edge of EE by 0.7 to get a CE domain edge of 0.7. Sum all the effected edges going to *HumanD* to get a CE edge of 1.06. After normalizing to 1.0, a probability distribution for the particle has it so that there is a 33.75% chance of the particle going to *HumanB* and a 66.25% chance of the particle going to *HumanD*.

DDD works effectively when each domain has a connectivity of ~3. When an organization has a simple problem space, such that there are a limited number of problem domains, simple domain edges suffice. When an organization grows and the problem space accrues a set of domains of size n, each node, using simple domain edges would be required to supply 3n relationships. The effort required of the individual can be impractical and therefore domain matrices provide a means by which an individual can relate domains in much the same way individuals relate each other.

4.1.3 The Full Decision-Making Network

The organization, thus far, can be seen as collective mental model distributed over all the individuals in the organization. The organizations domains are individualistically represented in a subjective manner much like the relative skill of each individual is a measure of the collective realization of each individual in the group. The distributed nature of the collective data structure lends to a scalable implementation of DDD in a societal-scale decision-support system.

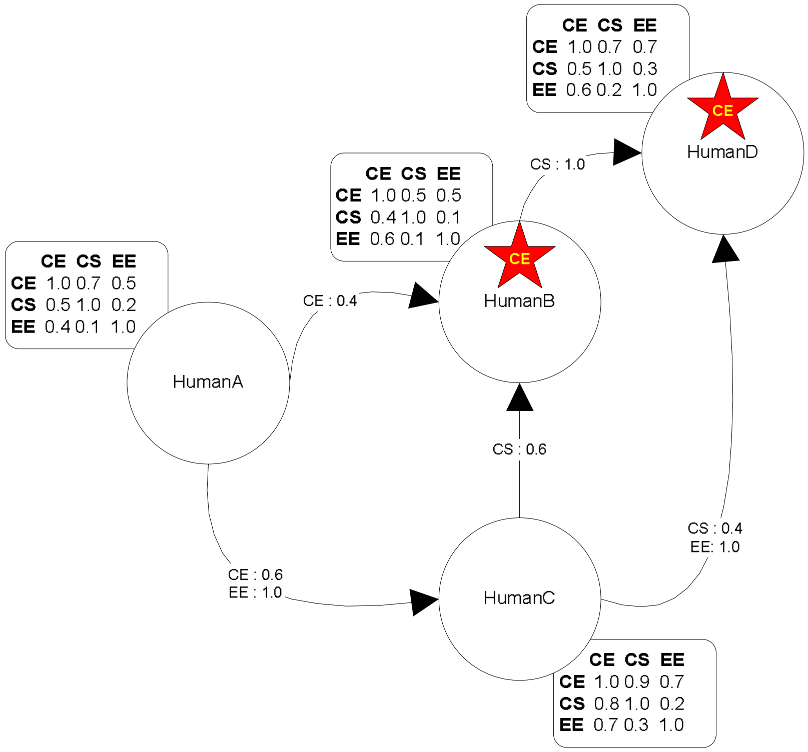


Figure 15: Distributed Data Structure of the Decision-Making Network

4.2 Determining an Individual's Energy Potential

DDD, thus far, has been described as a decision-making network capable of weighting the relative influence of participating individuals. A modified version of DDD can also be used to determine the relative influence that an individual has in any domain. This information is practical for two reasons. First, *an individual is able to determine their greatest area of influence* and therefore are able to gravitate towards problem-solving process where they have greater expertise (i.e. higher influence). Second, *the system can automatically determine competent individuals for the purpose of task-distribution* or other domain-specific processes.

If DDD is run without explicit reference to an active population, then each node will always distribute energy over its preference model and, in such a scenario, particles in the network never settle. Similar to Markov decision chain research (Hernandez-Lerma & Lasserre 1999)(Bar-Yam 1997), the network may reach an ergodic state in which the energy distribution in the network has settled into a stable pattern even though the particles never rest. This stable energy distribution within a particular problem-domain provides an individual with a measure of their ability relative to all other individuals in the group. For networks where stability never occurs, averages over oscillating patterns can be used. Completely random energy patterns would not benefit the system in discovering expert individuals (Steinbock and Rodriguez 2004). Furthermore, utilizing multiple problem-domains and taking advantage of non-active DDD allows individuals to create high-level expertise constructs for finding and individual who are competent over multiple domains (Mockus & Herbsleb 2002).

5 FUTURE WORK AND CONCLUSION

This section provides the reader with a glimpse of how these ideas may be implemented and tested in a real-world situation comprising human participants.

5.1 Development of a Distributed Decision-Making System

When designing a societal-scale decision-making system, scalability is of utmost importance since large-scale participation is its main use. At first glance, the development of such a system would depend on an agent-based design philosophy where a software agent represents each individual human. This software agent would not only maintain the preference model and domain matrix of the human it represents, but may also maintain a portion of the collective workspace. A distributed system would ensure that the collective workspace is seen as the union of all models across the agent population. The agents in such a system would function as the disseminators of both representative energy and workspace models. Such a design would provide the necessary peer-to-peer architectural model needed for scalability to the population at large.

5.2 Experimental Design with Human Subjects

The function of a societal-scale decision-making system can have two practical applications. Firstly, such a system could be used by an organization to leverage the collective-intelligence potential of members such that the organization could yield high-quality solutions to the problems it perceives. Secondly, for more opinion-based organizations such as political institutions, such a system could be used to better model the collective perspective of the group. Though the simulation demonstrated DDD as a useful algorithm for opinion-based systems, a more rigorous experimental framework will be needed to test the collective-intelligence abilities of the system. A preliminary sketch of a human subjects experiment for a domain-specific problem was demonstrated in a previous publication (Steinbock et. al., 2002). Since a societal-scale system would be based on a wide problem-space, an augmented experimental design would be needed that encompasses many problems from various domains and where the human subject pool is eclectic in their relative abilities across all tested domains.

McGraw-Hill®, in 2002, asked our collective intelligence research group to aid in the development of a system that would allow any individual in the world to participate in the generation of problems for the standardized test development area of their organization. McGraw-Hill® makes standardized tests for various domains such as Spanish vocabulary, English literature, geometry, earth science, etc. This atmosphere provides the necessary large problem-space range that would be seen in a general-purpose societal-scale implementation. Also, with any individual in the world being able to participate, the use of DDD to weight the relative influence of heterogeneous individuals across all problem domains would be needed. The system desired by McGraw-Hill® seems well suited as a preliminary test-bed for the future development of more sophisticated societal-scale systems.

5.3 The Societal Superorganism

Function	Organism	Society	SSDMS Components
Sensor	Perception apparatus	Reporters, researchers, …	Problem modeling
Channel and Network	Nerves, neurons	Communication mediums	Computer network
Associator	Synaptic learning	Scientific discovery, social learning	Solution modeling
Memory	Neural memory	Libraries, collective knowledge, …	Problem-space and solution-space
Decider	Higher brain functions	Government, voters, …	Decision-making
Effector	Muscle nerves	Executives	Solution Implementation

Table 3: Societal-scale decision-making system as the Societal Superorganism framework

Heylighen (2000), based on living systems work by Miller (1978), has made reference to human society as a superorganism carrying out the analogous behaviors of its human constituents. The functional components of an organism (sensation, memory, etc.) have a macroscopic realization when scaled to the society at large. In this work, a societal-scale decision-making system serves as an implementation potential for realizing a more efficient means by which society can carry out its information-processing behaviors—thus providing the framework for the network-based 'Global-Brain' argued by Heylighen (1997). Through an implementation, the ability for the group to make greater use of the collective intelligence potential of the society can be realized in the sense that the decision-making no longer has to be centralized to geographic regions (i.e. state and national capitals), but instead can be unified by a network infrastructure capable of utilizing every humans unique abilities to model problems, model solutions, decide amongst alternatives and finally distribute implementation tasks.

5.4 Conclusions and Summary

The work presented in this thesis has impact for the future development of societal-scale decision-making systems. Such systems will find themselves useful in institutions hoping to make use of the collective intelligence potential of the individuals comprising that institution. Also, as network technologies come to support the policy-making infrastructure of political institutions, such decision-making systems may provide a more accurate representation of the collective's perspective on policy issues. Future work in the deployment of this system for its potential as a human-collective problem-solving system will provide an experimental backdrop to gauge the relative significance of these ideas and to provide incentive for the development and deployment of these ideas in real-world institutions.

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