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Polarization and opinion analysis in an online argumentation system for collaborative decision support

Ravi Santosh Arvapally

Department: Computer Science

POLARIZATION AND OPINION ANALYSIS IN AN ONLINE ARGUMENTATION SYSTEM FOR COLLABORATIVE DECISION SUPPORT

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RAVI SANTOSH ARVAPALLY

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Approved by:

Xiaoqing (Frank) Liu, Advisor
Wei Jiang
Maggie Cheng
Sriram Chellappan
Donald C. Wunsch II

ABSTRACT

Argumentation is an important process in a collaborative decision making environment. Argumentation from a large number of stakeholders often produces a large argumentation tree. It is challenging to comprehend such an argumentation tree without intelligent analysis tools. Also, limited decision support is provided for its analysis by the existing argumentation systems. In an argumentation process, stakeholders tend to polarize on their opinions, and form polarization groups. Each group is usually led by a group leader. Polarization groups often overlap and a stakeholder is a member of multiple polarization groups. Identifying polarization groups and quantifying a stakeholder's degree of membership in multiple polarization groups helps the decision maker understand both the social dynamics and the post-decision effects on each group.

Frameworks are developed in this dissertation to identify both polarization groups and quantify a stakeholder's degree of membership in multiple polarization groups. These tasks are performed by quantifying opinions of stakeholders using argumentation reduction fuzzy inference system and further clustering opinions based on K-means and Fuzzy c-means algorithms.

Assessing the collective opinion of the group on individual arguments is also important. This helps stakeholders understand individual arguments from the collective perspective of the group. A framework is developed to derive the collective assessment score of individual arguments in a tree using the argumentation reduction inference system. Further, these arguments are clustered using argument strength and collective assessment score to identify clusters of arguments with collective support and collective attack.

Identifying outlier opinions in an argumentation tree helps in understanding opinions that are further away from the mean group opinion in the opinion space. Outlier opinions may exist from two perspectives in argumentation: individual viewpoint and collective viewpoint of the group. A framework is developed in this dissertation to address this challenge from both perspectives.

Evaluation of the methods is also presented and it shows that the proposed methods are effective in identifying polarization groups and outlier opinions. The information produced by these methods help decision makers and stakeholders in making more informed decisions.

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1. INTRODUCTION

In a collaborative decision making environment, stakeholders exchange arguments and undergo a dialogue process while closely deliberating on solution alternatives of a decision making issue. The intelligent argumentation system allows stakeholders to post issues, solution alternatives, arguments, and evidences in an argumentation tree and enable intelligent analysis of argumentation networks for collaborative decision making. The intelligent argumentation system assists stakeholders in capturing their rationale through argumentation.

Argumentation from a large number of stakeholders often produces a large argumentation tree. It is hard to comprehend such an argumentation tree without intelligent analysis tools. This dissertation presents new methods that employ clustering techniques and fuzzy logic to mine valuable information from huge argumentation trees. The valuable information provided by these methods could provide a solid support for collaborative decision making.

Four research challenges in the area of intelligent argumentation analysis for collaborative decision support, which are not addressed in existing research works, are identified. According to research work in social science, stakeholders in decision making groups tend to polarize based on their opinions. They tend to form groups with or without the knowledge or intent of the stakeholders. Identifying these groups helps decision makers and other individuals in the group to analyze the impacts of polarization groups in a decision making process. An innovative approach [1, 2] is developed to compute the aggregate thought of a stakeholder for each solution alternative by aggregating the argument strengths of each stakeholder after the argument inference. The aggregate thought of every stakeholder for each solution alternative under a decision making issue is derived and represented in the opinion dimensionality. K-means clustering algorithm [3] is employed to group the stakeholders in the argumentation process based on the similarity of their opinions [1]. Stakeholders who have similar aggregate thoughts are clustered into groups. Polarization groups are detected to support collaborative decision making. The proposed method is evaluated using data sets from experiments that were conducted. A method was also developed to identify leaders in each polarization group, by capturing the interactions among the members in each polarization group. The detection and analysis method of polarization is based on an assumption that, a stakeholder belongs to only one polarization group.

However, after investigating the experiments, it is realized that the polarization groups overlap and each stakeholder is a member of multiple polarization groups to a varied degree of membership. This issue is addressed [4] by employing the fuzzy c-means clustering algorithm [5] instead of the K-means clustering algorithm. The new method identifies polarization groups in argumentation for collaborative decision making and is able to compute degree of each stakeholder's membership in polarization groups. This additional information provided can further help decision makers in analyzing social dynamics that exist in the collaborative decision making.

The third issue deals with analyzing and computing aggregate thoughts of arguments on individual arguments, which represent individual thoughts, in an argumentation tree and further classifying those arguments. Stakeholders present their viewpoints in the form of arguments; however it is crucial to know what other participants in the decision making group think about those arguments. A novel approach [6] is developed to derive collective determination of an argument based on the total support and attack that an argument receives in the argumentation tree using fuzzy inference system [7]. The collective determination value and the strength of an argument are used to analyze the relationship between aggregate thought and individual thought of arguments. The collective determination value is derived for all arguments in the argumentation tree. Arguments are then clustered based on their strength and collective determination using the K-means clustering algorithm [3]. The decision makers will be able to identify and analyze clusters of arguments with opposing and supporting collective thoughts versus their individual thoughts. The proposed method was evaluated [6] using a data set [8] from experiments that were conducted earlier.

The fourth research challenge deals with identifying outlier opinions from a discussion group based on their argumentation carried out under an argumentation tree. The process of outlier opinion detection is performed from two different perspectives: individual view-point and collective view-point. First, the framework [9] computes the aggregate opinion of each stakeholder across all positions and an outlier detection algorithm is applied to generate top-k outlier opinions. This process is based on the individual view-points of stakeholders. In the second step, the aggregate collective determination score received by stakeholders through their arguments across multiple positions are computed. An outlier detection algorithm is applied to generate top-k outlier opinions. This process is based on the collective view-points of the group. The opinion which is farther away from the mean opinion of the group in the opinion dimensionality is considered as an outlier opinion. This framework is evaluated and validated by human subjects [9].

An empirical study [10] is conducted to evaluate the intelligent argumentation system by comparing it with email list-server for collaborative decision support. In addition, the application of intelligent argumentation system for collaborative decision support in the air traffic management [11] is investigated.

This dissertation explains in detail each research challenge mentioned above and proposes unique approach to address each challenge including experiments and related case studies.

Chapter 2 presents literature work on computer supported argumentation systems and the intelligent argumentation system. Sections 2.1, 2.2, and 2.3 are the contribution of other researchers. Chapter 3 presents hard polarization assessment research, and Chapter 4 presents fuzzy polarization assessment framework. Chapter 5 presents research work on individual thoughts and collective thoughts of arguments. Chapter 6 presents research work on identifying outlier opinions in an argumentation tree. Chapter 7 presents air-traffic management case study, and empirical evaluation of argumentation system and email system for collaborative decision support. Chapter 8 concludes the dissertation. Sections 3.3, 4.3, 5.3, 6.2, 7.1.2 and 7.1.3 discuss the literature work related to each research challenge presented. The datasets used in some experiments are from Satyavolu's [8] empirical evaluation.

2. BACKGROUND

2.1. COMPUTER SUPPORTED ARGUMENTATION SYSTEMS

Argumentation is a central and essential element in human life for collaborative decision making. In the last forty years, several scientists have both proposed and developed various argumentation models and tools. Several of these tools are still in use today to support argument mapping. These tools, however, provide limited decision support through arguments.

An argumentation system that allows stakeholders to participate in the dialog process using a computer is known as a computer supported argumentation systems. Argumentation systems help stakeholders understand the rationale underlying a decision making issue. Argumentation systems support collaboration and it is preferable than other mass communication tools such as email, blogs for collaborative decision making [12, 13]. Argumentation systems address some of the challenges that other mass communication tools cannot [12, 13]. Argumentation models have been widely accepted and used for multi-agent communication, negotiation models, user modeling, and more [14]. Various formal and informal argumentation models have been introduced.

Argumentation models can be broadly classified into either formal or informal argumentation models. Formal argumentation models are logically sound though difficult in practice to use. Informal argumentation models are more usable in practice. The intelligent argumentation system follows Toulmin's informal argumentation model. Philosopher Stephen Toulmin proposed an informal argumentation model [15]. Many systems today follow this influential model. Additional models, such as Dung's abstract argumentation model, have also been proposed and extended. Many argumentation systems that have been introduced by researchers lately either follow the Toulmin's argumentation model [15] or the Dung's abstract argumentation model [16, 17]. The intelligent argumentation system follows the Toulmin's model of argumentation and is an example of a weighted argumentation system, where the arguments carry strengths.

Issue based information system (IBIS) [18, 19] supports several argumentation elements, such as topics, issues, questions, positions, arguments, and model problems.

IBIS supports a variety of navigation and linking support in the argument diagram. Various notations are provided in constructing the argument maps [18, 19, 20]. The graphical issue based information systems (gIBIS) [19, 21] has been extended from the IBIS. The gIBIS system helps visualize issues and possible solutions to those issues over a local area network. The participants can present their issues and possible alternative solutions along with the arguments, either attacking or supporting the alternatives through their arguments. Both the IBIS and the gIBIS fail to provide efficient decision support to the group because they cannot directly assist in selecting the suitable position. Because the Web had not yet been invented when these systems were created, spatially located participants cannot gain access to argumentation trees.

SIBYL [22, 23] was proposed by Jintae Lee in 1990 for decision support. Lee was inspired by gIBIS. Lee's knowledge-based system was originally meant for managing group decision rationale through both arguments and support. It uses a semi-formal representation known as DRL (Decision Representation Language) [24] to represent the qualitative aspects in decision processes. DRL consists of elements such as alternative, goal, decision problem, claim (support, deny), and more. SIBYL constructs a decision matrix based on both the user's goal and alternatives. Cells in the table are initially set to 'unevaluated'. The decision matrix is updated as stakeholders participate in the argumentation process. The SIBYL system supports various associations among the nodes in the argumentation map. SIBYL also provides some special services, such as dependency management (monitoring decisions which depend on each other), plausibility management (the strength of supporting argumentation for an alternative), viewpoint management (arguments sharing common assumptions), and precedent management (other decisions sharing the same goal).

Gordon and Karacapilidis [25] proposed the Zeno argumentation framework, a semi-formal model of argumentation based on both Toulmin's informal model of argumentation and the IBIS model. The Zeno system both computes and produces information about the relative quality of the alternative positions of a decision issue given by a participant. This information can be useful in making more appropriate decisions. Zeno is built upon dialectical graphs. It supports semantic labeling of the components in the dialectical graph, critical in argument inference [25, 26].

Karacapilidis [27] extended the Zeno argumentation framework, introducing HERMES. The HERMES system is a famous classic example of an argumentation system. HERMES [27] is a computer supported argumentation and collaborative decision making system which is an extended version of Zeno's argumentation framework [25]. HERMES and Zeno are inspired from the informal model of IBIS. The HERMES [27, 28] argumentation system was supported by the World Wide Web. Because HERMES runs on the Web, people from across the globe can participate in the argumentation discourse. HERMES supports the multi-agent decision making process in which agents can participate in the argumentation process. Stakeholders can build a discussion graph by exchanging arguments. The discussion graph is in a hierarchical structure. Each post in the forum corresponds to argumentation elements. Issues, alternatives, position (position in favor, position against), constraint, and alternative constraint are the elements of the discussion graph in HERMES.

A position in this system is synonymous with an argument, can be either in favor of another argument or against an argument. A position in favor signals that an argument supports other arguments. A position against signals that an argument attacks other argument. Both the priority relationships and the preference orders between arguments in the discussion graph are described quantitatively. Hence, this system provides an opportunity to assess the alternatives and issues quantitatively.

HERMES uses the constraints for analyzing the positions and alternatives in an argumentation tree. These constraints produce the preference relationships among the positions. The system provides two different labels for the positions: 'active' and 'inactive'. The labeling process assists in decision making by providing an inference of positions in the tree. The arguments' weights are used to compute the alternatives' weights. The range for the argument components is between 0 and 10. Any argument component is, by default, given a value of 5. The alternative with the highest weight is the winning alternative among the provided alternatives. Hence, the HERMES system provides collaborative decision support. HERMES system constantly looks for inconsistencies among arguments. Each and every element has an activation label. Status on the activation label is changed based on different definition standards. Another version of the HERMES [28] system provides multi criteria decision making [29]. The major problem with HERMES is its inability to support fuzzy associations between the positions. In reality, these relationships are very fuzzy by nature.

Klein [30, 31, 120, 122] presented some important challenges and serious limitations associated with Web-logs, discussion forums, Wikis, and more. Disorganized content, low signal-to-noise ratio, quantity rather than depth, polarization in groups, and dysfunctional argumentation are just some of the challenges he described. Klein [31] introduced Deliberatorium [31] for large scale deliberation to address some of these problems. Deliberatorium is an argumentation system that supports a large number of stakeholders discussing wicked problems.

Although the argument maps in the Deliberatorium are well structured and presented, the decision support received is limited. Participants in this system can rate ideas. These ratings can address redundancy to a fairly good extent. Rating ideas is explicitly provided by participants. It is more intuitive, however if the rating is provided by an argument associated with that particular idea in the argument map.

Both Karousos and Karacapilidis [32, 33] developed CoPe_it, a Web-based argumentation system for collaborative learning. CoPe_it allows stakeholders to participate in the argumentation process and thereby support discourse for knowledge sharing. Stakeholders using CoPe_it build knowledge graphs. These graphs assist in both decision making and collaborative learning sessions. CoPe_it allows multiple users to participate in the argumentation process. CoPe_it may support either an alternative or an argument by quantifying the posts in a knowledge graph. CoPe_it could consider several social parameters, stakeholder preferences numerically, position strengths and more to assist in collaborative decision support.

The MIT Collaboratorium or Climate CoLab [30, 34, 35] and MIT Deliberatorium [30, 31] are the tools that support a group of stakeholders to present their issues and carry out discussions. The MIT Climate CoLab [36] is computer-based collaborative system that supports discussion forums, voting, and model-based simulation. Climate CoLab is one of the largest online communities to work collaboratively with other stakeholders. This system was introduced to the public to discuss climate change problem over the internet. The stakeholders exchange their views and opinions in the form of arguments. They also participate in voting procedures. This system provides limited decision support.

Araucaria is argument diagramming software that supports stakeholders in building the argument tree, analyzing and representing the arguments [14]. The Araucaria argumentation system is built upon the rhetorical structure theory, supporting various argumentation schemes. The user has the freedom to choose his argumentation scheme. Because stakeholders should understand the argumentation system, they should know which scheme is more appropriately suitable for their situation. This tool provides good flexibility in both constructing and diagramming the arguments.

Argumentative [37] is another argumentation system that allows stakeholders to post their issues. Stakeholders can post their premises, reasons and objections. Every node in the tree has a comment attached to it. These comments describe the meta-data of that node, present the author of the element, date, and more. Argumentative is open source software. It follows the informal argumentation models with great visualization ability.

Compendium [38] supports argument mapping inspired by the IBIS system. It was developed for both policymakers and information management in general. Truthmapping [39], Idea [40], and Debategraph [41] are Web-based argumentation systems available for free on the World Wide Web. These systems are built to support online debates. They follow a tree structure for the representation of the information. Although they provide limited support in the context of both argument analysis and decision support, they are more advanced and organized than either blogs or forums for collaborative work.

Over the past few years many researchers have introduced several models and systems in various application domains [25, 27, 42] for argumentation and carried out several experiments [30]. Existing argumentation systems support collaborative decision making. These systems, however, provide very limited decision support in a collaborative environment. Some systems provide support by constructing argumentation diagrams and visualizations. Many argumentation systems were built for understanding design rationale. Some systems are meant for students to assist them with critical thinking. Others provide quantitative information based on the arguments' ratings and weights.

Some argumentation systems provide better navigation within the argumentation map. HERMES and the intelligent argumentation system can also provide support in the form of multi criteria decision making. The intelligent argumentation system provides additional decision support information on par with other existing argumentation systems.

2.2. INTELLIGENT ARGUMENTATION SYSTEM

Sub-section 2.2.1 presents an overview, 2.2.2 discusses the elements of an argumentation tree and sub-section 2.2.3 presents the argumentation reduction fuzzy inference system.

2.2.1. Overview. This sub-section explains both the background of how the intelligent argumentation system was developed over the years and introduces the system.

Liu et al. [7, 43, 44, 45, 121, 123] are building the intelligent argumentation system for collaborative decision support for a long time. Several students worked and contributed to this project.

In 2003, Sigman [45] presented argumentation methodology for capturing and analyzing design rationale arising from multiple perspectives in collaborative environment. Sigman then built argumentation reduction fuzzy inference system to carry out the reduction process of an argumentation tree. In 2006, Raorane [7] worked on argumentation system for collaborative engineering design [7, 43] and resolution of conflicts. Raorane et al. [43] developed web-based intelligent argumentation tool as a part of the web-based collaborative engineering design system. Later in 2007, Zheng [44] developed methods for incorporating the priority of a stakeholder in the intelligent argumentation system. The priority of a stakeholder was used to re-assess the strength of an argument using fuzzy logic based inference system. Zheng et al. [7, 44] also developed mechanism for detection of self-conflicting arguments.

Khudkhudia [46], in the year 2008 incorporated evidences in the argumentation tree. Stakeholders can post evidences supporting their arguments and evidences under an argument are aggregated using the Dempster Shafter’s combination rule. Khudkhudia also developed a fuzzy based approach to reassess the strength of an argument based on the support it has from the evidence. In 2009, Satyavolu [8] developed a novel fuzzy based approach to assess the priority of a stakeholder in a group, based on his contribution towards the winning and non-winning positions in an argumentation network. Satyavolu [8] also conducted experiments using intelligent argumentation system in software engineering class to evaluate the mechanism she developed.

Wanchoo [47] developed a computational argumentation model to support multi-criteria decision making using the intelligent argumentation system. Wanchoo [48] conducted experiment in the software testing and quality assurance class in spring 2010.

2.2.2. Elements of the Argumentation Tree. The intelligent argumentation system allows stakeholders to post a project, issues, and alternatives in the argumentation tree over which argumentation process is carried out. Figure 2.1 presents an example of a position dialog graph.

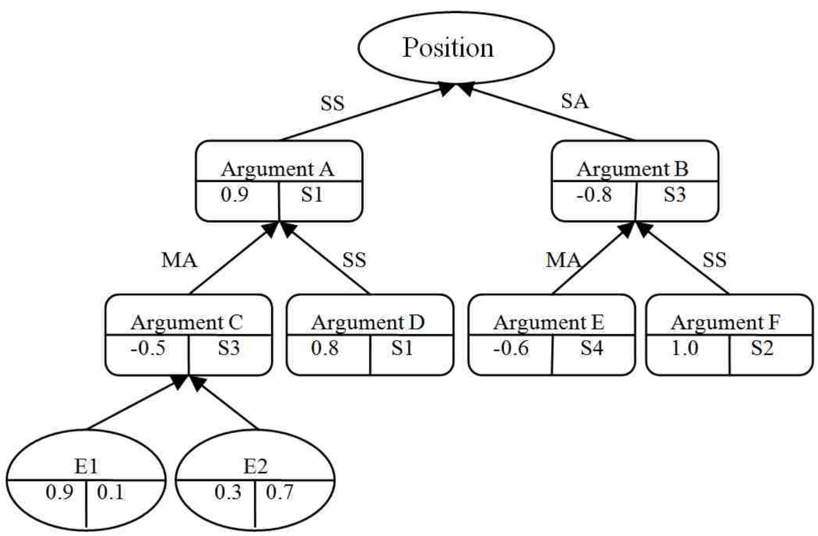


Figure 2.1. Position Dialog Graph

Project - Project node (P) is the root node in an argumentation tree, where the project details and stakeholder details are posted. Any stakeholder can post a project, and under the project node, any number of relevant decision making issues can be posted.

Issue - Issue node (I) is at the second level in the argumentation where a stakeholder can post concerned decision making issues. These decision making issues are relevant to that project. A decision making group can participate in several decision making issues related to a project. The decision issues we are discussing here are very strategic that have high importance to an organization. These issues are usually cognitively complex. The results from these decisions affect several others financially and economically. Position or alternative solutions are posted under the node issue in the argumentation tree.

Position - Positions are the alternative solutions that are posted under the issue in the tree, see Figure 2.2. Since the positions provide the stakeholders to explore the solution space through interactions, any number of positions can be posted under an issue. Arguments are either directly or indirectly associated to a position node.

Argument - Every argument carries a strength which expresses its association with its parent node. Stakeholders are also responsible for posting strength of an argument explicitly along with their argument. The strength of an argument ranges from -1 and +1. A negative strength conveys that the argument is attacking its' parent argument, an argument with positive strength conveys that the argument is supporting its parent node, and an argument with strength zero expresses its' indecisiveness. Stakeholders can strengthen their arguments posting evidences supporting their arguments. A stakeholder can post any number of arguments supporting or attacking other arguments or positions already posted in a tree. Based on the strength of the argument, the system identifies labels such as medium support (MS), strong support (SS), Indecisive (I), medium attack (MA), and strong attack (SA). The labels are linguistic terms whose semantics are captured by their membership functions. The degree of strength of an argument posted by their owners will be used for fuzzy inference by the fuzzy inference engine based on fuzzy inference rules using the labels.

In Figure 2.1, A, B, C, D, E and F are the arguments posted by stakeholders along with the degree of strength of the argument. The strength presents the association between an argument and its parent node. SS, SA, MA refer to strong support (SS), strong attack (SA), and medium attack (MA) respectively. More discussion is provided about these labels in the following sub-section.

Before the argumentation process, stakeholders initially have an idea and an opinion towards the decision problem. As the argumentation process unfolds, they get to know the opinions and views of other stakeholders. In the process, stakeholders also have the opportunity to express their arguments on other individual's arguments. Contrasting opinions lead to conflicts and resolving conflicts leads to refining the opinions of stakeholders. At the end of the process, consensus will be developed among stakeholders. This exchange of information in groups leads to collective decision making.

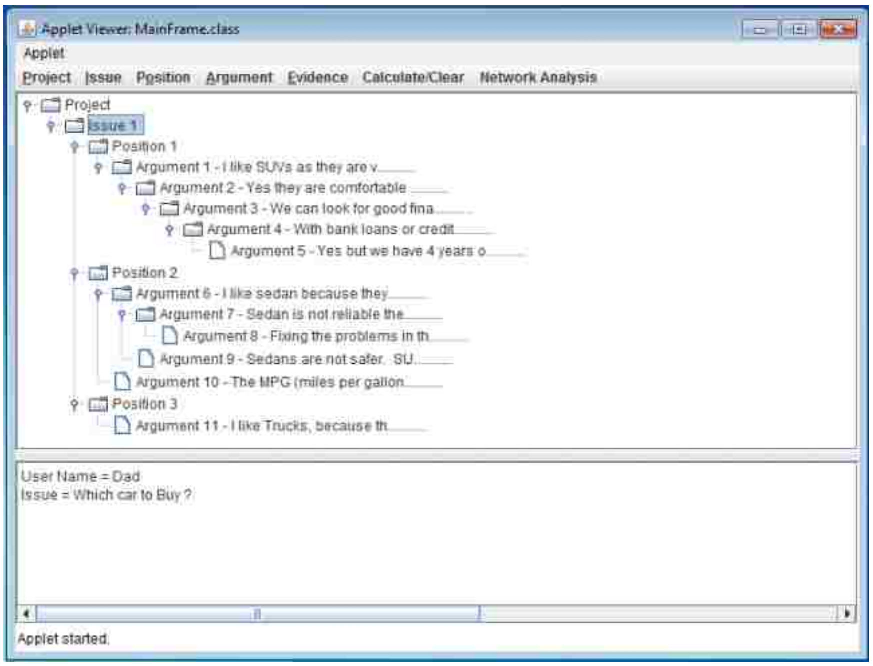


Figure 2.2. A snapshot of Intelligent Argumentation System

2.2.3. Favorability Assessment through Intelligent Argumentation. The argumentation reduction fuzzy inference system is used to assess the impact of arguments in the argumentation tree on a position. Arguments in the argumentation tree are reduced level by level in a tree based on the fuzzy inference heuristic rules. This process is carried out on all the arguments in a tree. These arguments are inferenced level by level such that all the arguments are directly associated to its position respectively. As all the arguments of a tree are directly associated to its respective position, the favorability factor of a position is computed by aggregating the strengths of the arguments associated with a position [7, 49].

Both the strength of an argument and the strength of its parent argument are provided as inputs to the fuzzy inference engine. Child argument and parent argument are put on the same level of an argumentation tree based on the inference. The child argument is reduced by one level in the tree such that both arguments are siblings, providing a new strength value which is relative to its parent argument. Based on the fuzzy membership functions, these strength values undergo fuzzification process. The output from the fuzzification process is given as input to the fuzzy inference engine, and appropriate fuzzy rule is applied from the fuzzy rule base for inference. Based on the rule, a relative strength value is derived with respect to its parent argument. This new score undergoes the defuzzification process. In the defuzzification process, the obtained inputs are converted to crisp outputs, see Figure 2.3. For further information on fuzzy argumentation inference system, please read our papers [7, 49].

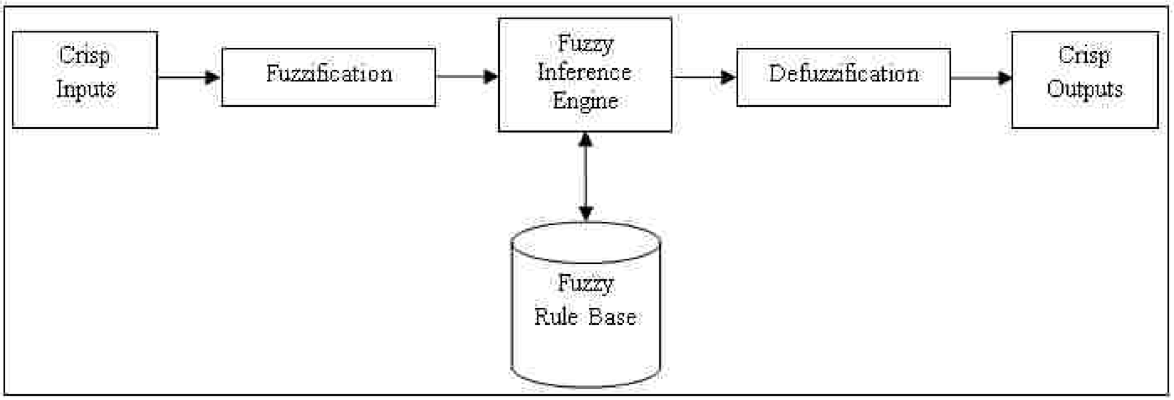


Figure 2.3. Fuzzy Inference System

The reduction process is carried out based on the following general fuzzy heuristic rules which are further extended to twenty-five rules based on different membership functions. The following four fuzzy heuristic rules are used in the fuzzy knowledge base for the argument reduction [7, 49]:

If argument B supports argument A and argument A supports position P, then argument B supports position P.

If argument B attacks argument A and argument A supports position P, then argument B attacks position P.

If argument B supports argument A and argument A attacks position P, then argument B attacks position P.

If argument B attacks argument A and argument A attacks position P, then argument B supports position P.

In the argumentation reduction process, the strength of arguments that were indirectly associated to a position are reassessed. This reassessed strength is relative to its new parent node. After the argumentation reduction process is completed, the favorability factor of each position is computed by aggregating the strengths. The favorability factor produced by the system for each position represents the favorability of the decision making group for that position. The higher the favorability factor of a position is, the more favorable it is to the group. Figure 2.4 presents an example of the fuzzy inference based argument reduction in an argumentation tree. For more information about the intelligent argumentation system, please refer to articles [43, 49].

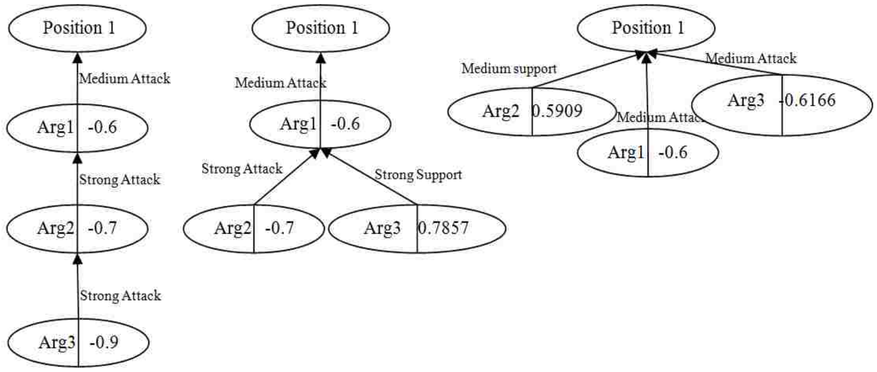


Figure 2.4. Fuzzy Inference based Argumentation Reduction Example

3. HARD POLARIZATION ASSESSMENT

3.1. PROBLEM DESCRIPTION

Complex issues within organizations require strategic decisions be made for a good cause. An argumentation process allows stakeholders to debate with peers for a given issue. Stakeholders in a decision making group usually have their own choices of support for a given issue. As a result, stakeholders with similar opinions tend to become closer by both supporting one another and attacking others. These groups then influence other stakeholders, encouraging them to change their opinions [50, 51].

A group of stakeholders may share similar opinions for a given issue, exchanging arguments with other stakeholders in a collaborative decision making process. These stakeholders are part of a polarization group. Typically, a group is headed by a leader who plays a crucial role. In our case, we consider the stakeholder with the highest group support to be the leader. Identification of polarization groups and leaders in argumentation becomes an important challenge which has not been addressed in the past. The polarization assessment in argumentation provides the decision maker with information about the groups and their opinions towards the given issue. The process of identifying both groups and their leaders is new to argumentation systems and collaborative decision making paradigms.

In this section, a method for identifying polarization groups and leaders in an argumentation process using the K-means clustering algorithm is presented.

3.2. SIGNIFICANCE OF THE PROBLEM

An argumentation process is a complex system involving many social agents exchanging arguments. The social dynamics in an argumentation process are very complex as they involve both the stakeholders' personal belief as well as their relationships with others. A stakeholder's opinions may evolve as they become influenced by others [48]. Identifying both polarization groups and their leaders helps decision makers understand the objectives of individual polarization groups. Identifying polarization groups helps decision maker understand their impact on decision alternatives. It also can help a decision maker judge the post-decision effects on both individual groups and their leaders. This information could assist decision makers in making a more in-depth analysis of the positions and taking more appropriate decisions.

Consider a hypothetical situation in which an important, controversial bill must be passed in the senate. This bill is of economic interest to the nation. The senators and policymakers are the stakeholders in the argumentation system. One of these political parties supports the bill and the other opposes it. These stakeholders belong to either political party A or party B. These stakeholders can use the argumentation system to resolve decision making issue. Individual stakeholders honor the decision made by their respective parties on the bill. However, they still have their own personal opinion. This opinion may be in contrast with the opinion of the party. Our proposed framework can identify both the polarization groups and leaders formed among the senators and policymakers. We can also identify the senators with contrasting opinions, both within the party and the opposition party. Finally, our framework provides flexibility for the decision maker in providing the number of polarization groups as an input.

Although only two political parties are in our given example, one might try looking for four groups. The decision maker can understand which political party is strong with their opinion. If three groups are formed within party A with contrasting opinions and if stakeholders in party B are all together in one group, we can understand that party B is stronger as senators in this party stand united, behaving loyally. In another case, we might think of stakeholders from party A as sharing their opinion with party B. In reality, many sub-groups may exist within a political party which might have contrasting opinions.

The decision maker has the freedom to both analyze and understand the closeness of the polarization groups in terms of their opinion. In another instance, we might think of party A's opinion as very close to that of party B. The leader of party A can analyze the interactions and social dynamics among the stakeholders in his party as well as those within the opposition's party. In even another case, some stakeholders from party A and some from party B might share the same opinion.

3.3. RELATED WORK

In this section, we present literature on the polarization assessment from a social science perspective. In social science literature, several scientists have referred to polarization, where participants in group discussions tend to polarize on their opinion. Polarization [51] is a phenomenon where people tend to form groups based on the similarity of their opinion. Sunstein [51] explained the phenomenon of polarization and its association with social cascades, and social influence. Klein [31] identified the existence of polarization in the social media systems and people with similar opinion or who share same opinion tend to form in to groups and they only see a subset of the issues and ideas. Hence it is very important to identify the groups and the polarization group information is useful in decision making. The dynamic social impact theory proposed by Latane is a highly influential theory which presents the effects of other stakeholders on an individual stakeholder in a group during their interactions [52]. Latane proposed three different principles in the dynamic social impact theory: (a) the social impact or influence received by a target stakeholder in a group is because of the social forces i.e., other stakeholders in the group, (b) as the strength of the social forces increases, the influence also increases and (c) when more stakeholders join the individual targeted stakeholder, the total influence received by this newly formed target group is diluted among the stakeholders in the group. Hence, the impact is reduced [52]. Dynamic social impact theory holds for a group of stakeholders in the debate process and the argumentation process where the influence is presented through the arguments and the arguments' strength. In his extended research work, Latane proposed that the groups formed are not static but they keep changing throughout the discussion process because the stakeholders change their opinions when exchanging arguments [48, 53]. As the arguments among the stakeholders are exchanged, the opinions of the stakeholders may change, and stakeholders with similar opinions form in to groups. Harton et al. demonstrated group dynamics and presented four group-level phenomena whenever people in spatially distributed groups, such as residents of an apartment complex or people at a banquet table, influence one another [54]. Consolidation, clustering, correlation and continuing diversity are the four group-level phenomena [50, 53, 54] that a group holds. The dynamic social impact theory states that stakeholders form groups, and these groups tend to polarize on issues based on their opinions. The stakeholders in these groups are the ones with similar opinions.

3.4. DECISION SUPPORT THROUGH POLARIZATION ASSESSMENT FRAMEWORK

We extended the intelligent argumentation system to support polarization assessment by capturing the stakeholders' rationale in their arguments. The argumentation system employs K-means clustering algorithm [3]. This algorithm is an unsupervised clustering algorithm for classifying stakeholders according to their favorability towards a position. The following sub-sections provide a detailed explanation on this system's framework.

3.4.1. Polarization Groups Assessment Framework. Argumentation tree is built as stakeholders exchange arguments. The tree evolves as the argumentation process is conducted. After the argumentation process, the framework is applied to the argumentation tree. This framework uses the argumentation reduction fuzzy inference system to derive the favorability of each individual stakeholder on all the positions. Figure 3.1 illustrates the framework of the proposed idea.

Inference system reduces the arguments to one level such that all arguments are directly associated with their respective position. Once all arguments are connected to the appropriate positions, the strength values of all arguments posted by a stakeholder under every position are accumulated. A stakeholder's favorability toward every position is then computed. This process is conducted for all stakeholders, for every position posted. After data is collected from the tree, it is normalized to retain consistency. The opinion of a stakeholder is represented by a numerical value. This value is the sum of the total support and the total attack of a stakeholder towards a position. It is calculated as follows:

Favorability factor of a stakeholder = (Total support for a position by the stakeholder) + (Total attack for a position by the stakeholder)

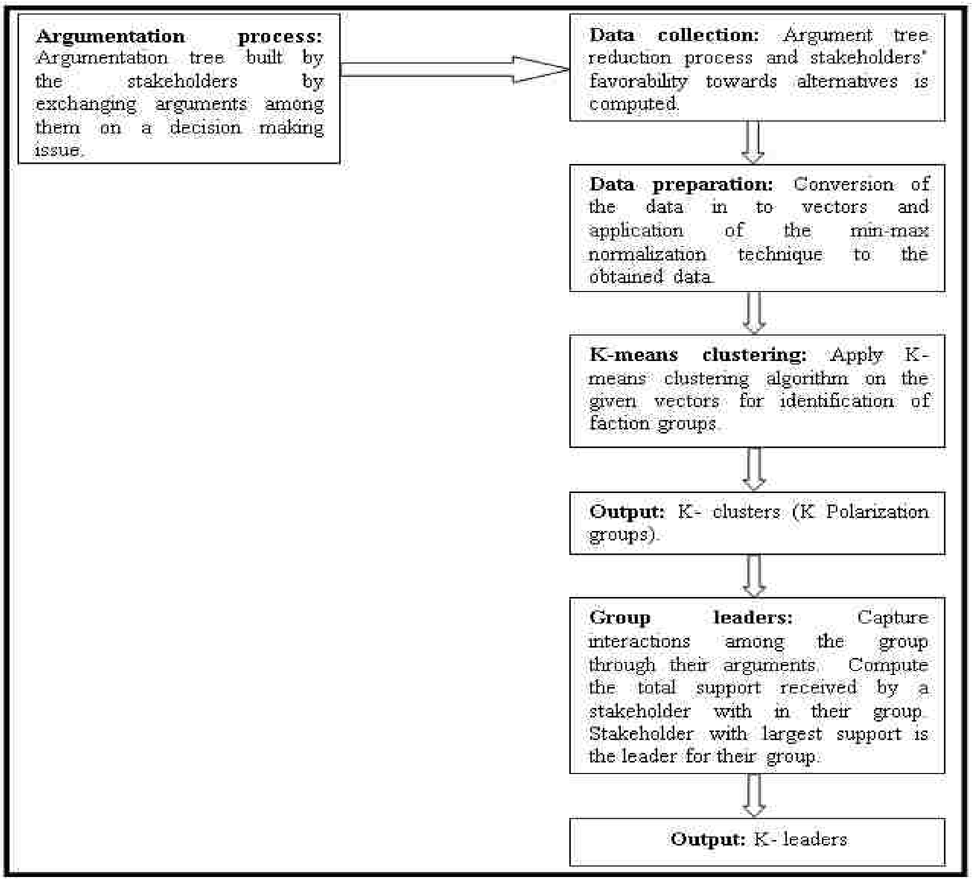


Figure 3.1. Framework of Polarization Assessment

The following formula (Eq. 1) was used to normalize the data. Normalization was conducted using the min-max normalization technique. Min A, and max A are the minimum and the maximum values in the data collected from the argumentation tree. New_min A and new_max A are the new range for the data provided. In our experiments, we used new_minA as -1 and new_maxA to 1. The stakeholder's opinion is represented with numerical values. The new range of the data will be from -1 to +1.

$$\boxed{v' = \frac{v - \min A}{\max A - \min A}(new\_\max A - new\_\min A) + new\_\min A} \quad (1)$$

The decision making issue in the intelligent argumentation system is represented by I_i, where i (i > 0) represents the number of issues in the argumentation tree. The stakeholders in the decision making group can add the positions in the tree under issue node I_i. The positions (alternatives) are represented by A_l, where l represents the number of positions under the issue I_i and is either greater than or equal to 1. Stakeholders in the decision making group are represented with S. S_j signifies the number of stakeholders, where $j \geq 1$. The arguments in the argumentation tree are reduced to one level in order to find F_{jl}. This value is the favorability value of stakeholder j for position l. The value of F_{jl} may be either negative or positive. Favorability factor depends upon the arguments posted by stakeholder S_j under position A_l. Based on the F_{jl}, one can understand a stakeholder's opinion. The following classification explains F_{jl} value better.

F_{jl} = Negative. Favorability factor signifies that stakeholder j is attacking position l.

F_{jl} = Positive. Favorability factor signifies that stakeholder j is supporting position l.

F_{jl} = Zero. Favorability factor signifies that stakeholder j has a neutral opinion regarding position l.

Every stakeholder (j) has a value towards position l. We use the min-max normalization method to normalize both the values and the range [-1, 1]. The F_{jl} values of each stakeholder (S) are presented as a vector. Vectors are provided as an input to the K-means clustering algorithm. Each element in a stakeholder's opinion vector refers to the favorability of a stakeholder towards a position. The favorability vector of stakeholder S_j when there are 'l' positions is represented in a vector as ($F_{j,1}$, $F_{j,2}$, $F_{j,3}$, …..$F_{j,l}$). For example, stakeholder S_2 has a favorability vector represented as ($F_{2,1}$, $F_{2,2}$, $F_{2,3}$, $F_{2,4}$…… $F_{2,l}$). $F_{2,1}$ presents the favorability of stakeholder 2 toward position 1. $F_{2,4}$ presents the favorability of stakeholder 2 towards position 4.

Figure 3.2 is an example argumentation tree built by three different stakeholders for issue 1. The argumentation tree has three different positions namely position 1, position 2, and position 3. Stakeholders have contributed to the decision making process by building an argumentation tree consisting of sixteen arguments. The arguments posted are directly associated with either a position or an argument.

Figure 3.2 presents the argumentation tree before the argumentation reduction process. Figure 3.3 presents the tree after the argumentation reduction process. All arguments posted by a stakeholder under a position are grouped together. The summation process is then conducted to derive the total favorability of those stakeholders for the respective position. When the arguments are reduced level by level, the strength of an argument is computed relative to the new parent argument. Because an argument is now directly connected with the position and the impact changes. Therefore, the strength of an argument is reassessed.

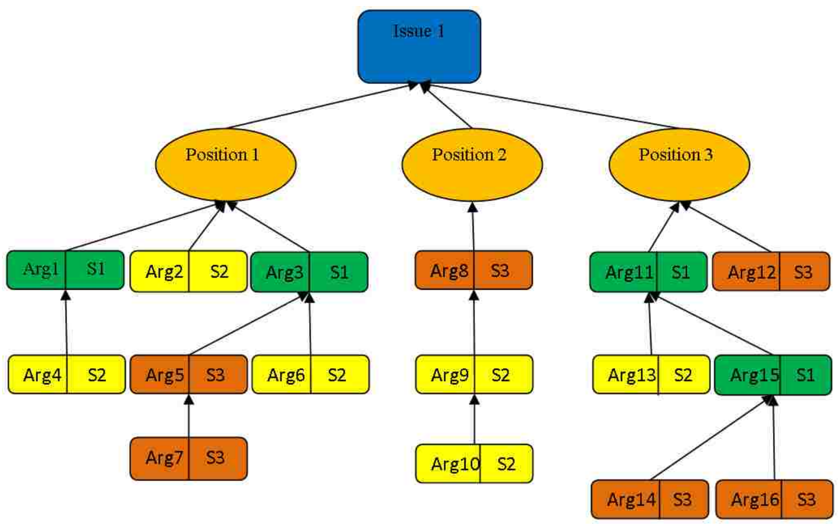


Figure 3.2. Argumentation Tree before Argumentation Reduction Process

This argumentation reduction process is carried out by the framework using the argumentation reduction fuzzy inference system. See section 2.2.3 for a detailed explanation about the argumentation reduction fuzzy inference system. The summation process is adding up of the strengths of all the arguments under a position posted by an individual stakeholder and, thereby, computing the total favorability of a stakeholder for a position.

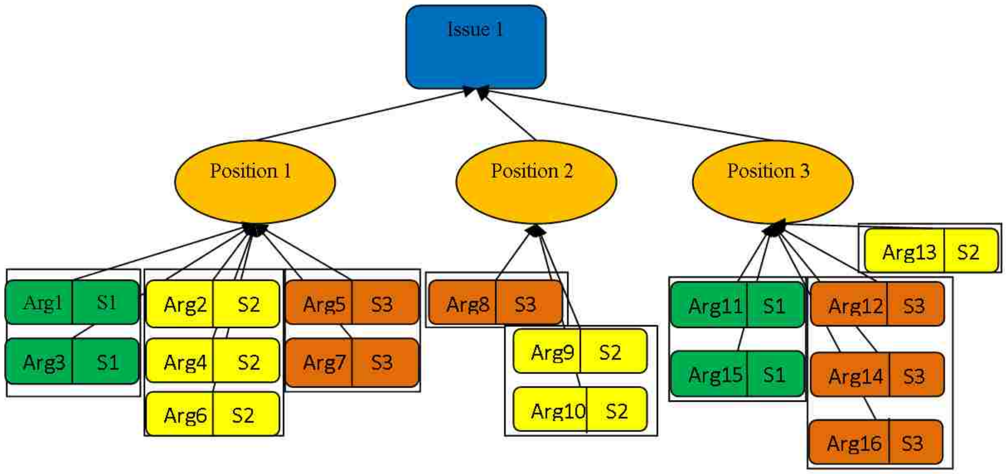


Figure 3.3. Argumentation Tree after Reduction Process

3.4.1.1 K-means clustering algorithm. The favorability factor of each stakeholder for all positions is represented as a vector. The Euclidean distance is used for similarity measurement between vectors. The K-means algorithm (Algorithm 1) randomly takes 'K' points as the initial centroids of the clusters. In each iteration, opinion vectors are compared with these 'K' centroids using the Euclidean distance. Each data point is assigned to a cluster, based on the distance between centroid and opinion vector. After each iteration, the centroid is updated by computing the mean of all vectors in that cluster. This process is carried out for all vectors for several iterations until convergence is achieved. Convergence can be evaluated by the mean square error within the cluster or when the data instances stop moving from one cluster to another [3, 55].

Once convergence is achieved, the algorithm stops. Algorithm then produces 'K' clusters, where each cluster has data points that are as close as possible to centroid. Each cluster produced by this algorithm is treated as a polarization group. They are clustered according to similar opinions. The value of 'K' should be provided by the decision maker as input to the algorithm. The decision maker must provide the 'K' value as how many groups he/she would like to see among the stakeholders. The value of 'K', however, is always less than or equal to N (i.e., the number of data instances).

The Euclidean distance (Eq.2) formula was used to compute the similarity measurement among participants. Values X1, X2, and X3 represent the favorability factors for position 1, 2 and 3, respectively, by stakeholder X. Values Y1, Y2, Y3 represent the favorability factors for position 1, 2 and 3, respectively, by stakeholder Y. This formula derives the similarity measurement among stakeholders X and Y.

$$(X,Y) = \sqrt{(X1 - Y1)^2 + (X2 - Y2)^2 + (X3 - Y3)^2} \qquad (2)$$

Algorithm 1. K-Means Clustering Algorithm

1. Initialize a K-partition either randomly or based on some prior knowledge. Calculate the cluster prototype matrix.
2. Assign each object in the data set to the nearest cluster C_l.
3. Recalculate the cluster prototype matrix based on the current partition.
4. Repeat steps 2 and 3 until there is no change for each cluster.

3.4.2. Polarization Leaders Assessment Framework. Identifying leaders in each polarization group is equally important. Because, each leader is representing a polarization group and he has the support from his group. This sub-section presents the framework for identifying polarization leaders. The framework produces ‘K’ polarization groups. Interactions among the stakeholders are captured through their arguments. The sum of the strength of the arguments posted by a stakeholder to other stakeholder in the same polarization group is computed. This provides the relationship among the stakeholders. The total support and attack received by a stakeholder from the rest of the group is aggregated. Some stakeholders might support their own arguments with other arguments. These interactions are also considered for a polarization group leader assessment. A stakeholder with the highest support from the rest of the group is acknowledged as the leader. In some cases, a tie may occur. When this happens, one stakeholder is randomly selected to break the tie. Table 3.1 illustrates a sample interactions table. Relationships among the stakeholders in a polarization group are presented.

Table 3.1. Polarization Group Relationship Table

	S_1	S_2	S_3	.	.	.	S_j
S_1	X						
S_2		X					
S_3			X				
.				X			
.					X		
.						X	
S_j							X
Total support	Ts_1	Ts_2	Ts_3				Ts_j

Total support (Ts) represents the total support a stakeholder receives from his group. The stakeholder with the largest T_s value in a group is considered the leader. In some instances, stakeholders might receive attack from the rest of the group. When this occurs, the total support value could be negative. Although, stakeholders in a polarization group share similar opinion. It is not necessary that a stakeholder receives support from his group.

Stakeholders in a polarization group share a similar opinion. The strength of either support or attack for a position, however, might vary. For example, opinion vector of stakeholder A is (0.9, -0.3, 0.5). Opinion vector of stakeholder B is (0.8, -0.2, 0.56). Stakeholders A and B share a similar opinion. The strength of their support and attack for positions, however is different. If two or more stakeholders within a group share the same value of support, we can randomly choose any stakeholder as the group leader. If no interactions occur among the stakeholders in a group, we can, again randomly choose any stakeholder as the polarization leader.

3.4.3. Analyzing Polarization Groups and Leaders. The intelligent argumentation system uses the polarization assessment framework on the argumentation tree. This system produces both ‘K’ polarization groups and ‘K’ polarization leaders. It is important for a decision maker to understand the polarization information. Each cluster produced by the framework represents a polarization group. These groups are represented by centroids. The centroid of a cluster is a vector. This vector represents the opinion of the polarization group.

As the decision maker knows the opinion of each polarization group, he can further identify the stakeholders associated with the polarization group, making rational decisions. The decision maker can study and analyze the post-decision effects on both each polarization group and each stakeholder. Additionally the decision maker can, possibly, analyze and understand either the personal benefits or the incentives received by stakeholders in polarization groups based on their opinion. This information helps in taking more informed decisions. By identifying a polarization leader in each group, the decision maker would know which stakeholder is the leader.

Since we know the opinion of each polarization group, we can check the dissimilarity measurement between polarization groups using the Euclidean distance metric.

3.5. EVALUATION

This section presents two different small scale studies carried out at Missouri University of Science and Technology. Results in the first study are validated by the participants. The second study summarizes three different experiments conducted based on a case study.

3.5.1. Empirical Study 1. In this experiment fourteen students from the e-commerce business class were recruited to participate in our study. Fourteen students played the role of stakeholders and participated by posting arguments in the argumentation tree. The team of fourteen stakeholders were provided with the background case study and the decision making issue to be resolved. After participating for around ten days, an argumentation tree was constructed which consisted of thirty five arguments.

3.5.1.1 Case study. The issue was about the death of Aaron Swartz [56, 57]. Aaron Swartz was an American computer programmer, writer, political organizer and internet activist. He founded the online group demand progress, known for its campaign against the stop online piracy act. Aaron was charged for downloading thousands and millions of articles illegally from JSTOR archive using MIT's open network. If proven to be guilty Aaron would face up to thirty five years of prison and a fine up to $1 million. On January 11th, 2013 two years after his arrest, Aaron hanged himself in his apartment.

Issue – What happened with Aaron Swartz? Who is at fault for Aaron Swartz killing himself?

Position 1 – The laws, attorneys and MIT who pushed the case?

Position 2 – Not anybody's fault. It's not the Government's or MIT's fault in anyway. The rules have to be followed in any means.

3.5.1.2 Objective and framework. The objective of this experiment is to evaluate the polarization assessment framework with a real world issue. The participating stakeholders are provided with a detailed background about the case and how to use the system. Each stakeholder is provided with a unique username and password to log-on to our intelligent argumentation system to participate in the discussion. Ten days of time was given to the stakeholders to participate in the dialog process. After the discussion process, the polarization assessment framework is employed on the discussion tree to identify the polarization groups. The results generated by the polarization assessment framework are given to the stakeholders to validate.

3.5.1.3 Process and observations. Fourteen stakeholders participated in the discussion process using the intelligent argumentation system which was followed by the application of polarization framework on the discussion. K value was provided as two when the framework was used on the argumentation tree. The framework identified two opinions and the polarization groups associated with those opinions.

Table 3.2 presents the polarization groups, opinions of each polarization group and stakeholders in each group. Stakeholders in polarization group 1 strongly supported position 1 and attacked position 2. Stakeholders in polarization group 2 supported position 2 and attacked position 1. Group 1 consists of ten stakeholders and group 2 consists of four stakeholders. The opinions of polarization groups 1 and 2 are contrasting, since they have opposing views on the decision making issue.

Table 3.2. Polarization Assessment Results

Polarization group	Position 1	Position 2	Stakeholders
Polarization group 1	0.890	-0.009	S1, S2, S4, S5, S6, S7, S8, S9, S11, S14
Polarization group 2	-0.250	0.075	S3, S10, S12, S13

The results produced by the framework are presented in Table 3.2. Table 3.2 was presented to the stakeholders and questions were asked to validate the results. The stakeholders were asked to give their opinion on the results produced by the system. Out of fourteen stakeholders eleven have agreed with the classification (polarization) information produced by the system. One stakeholder was neutral about the result and two disagreed with the result. The plot in Figure 3.4 explains the validation of the results.

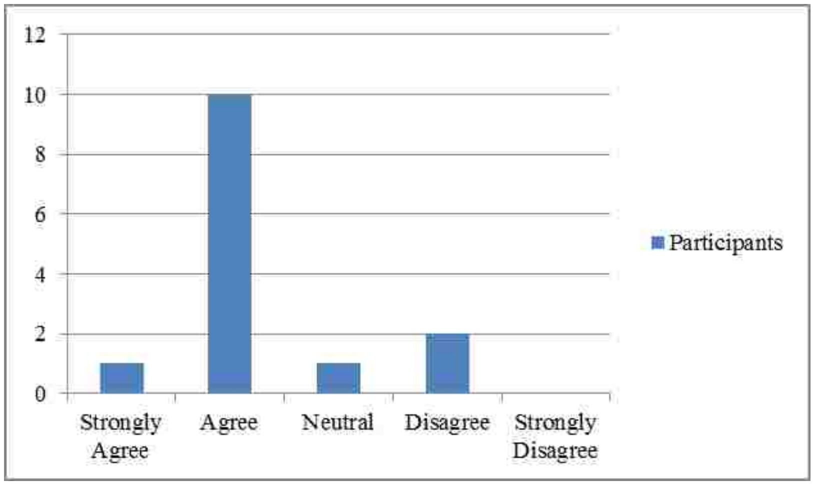


Figure 3.4. Participant's Opinion on the Polarization Assessment Results

3.5.2. Empirical Study 2

3.5.2.1 Objective. The objective of this experiment is to identify polarization groups and polarization group leaders in a decision making group to evaluate the effectiveness of the proposed framework. Earlier, Satyavolu [8] conducted an experiment by recruiting twenty four graduate students from a Software Engineering class at Missouri University of Science and Technology. These twenty four students played the role of stakeholders. The framework is applied on the argumentation trees built by those twenty four stakeholders.

Three experiments were conducted. All three experiments are related to the case study. Each experiment dealt with a decision making issue. The decision making issue was about the selection of software metrics program in an organization. This case study had three different scenarios. A software development project was given to a large scale, medium scale and small scale organization. Selecting appropriate software metrics program by each organization for the given project was the issue. The framework was employed on the three decision making issue trees constructed by the stakeholders. A detailed explanation on both the experiments and the results is presented in the following sections.

3.5.2.2 Case study. Adoption of software metrics program is a crucial aspect, and its' application to the software project development depends on various factors such as size of the organization, size of software project and many more. The decision issue in the first experiment dealt with the selection of a software metrics program for a large scale organization. The decision issue in the second experiment dealt with the selection of a software metrics program for a medium scale organization. The third experiment was about the selection of software metrics program in a small scale organization environment. No metrics program, light weight metrics program, and comprehensive metrics program are the three different positions provided for all three issues. In the 'no metrics' program, organizations do not adopt any software metrics program. Fewer than 35% of the artifacts are measured using a light weight metrics program. Between 35% and 60% of the artifacts are measured in the comprehensive metrics program. Because the three decisions issues were built upon a common case study, these three positions were the same for all three decision issues.

Position 1 – No metrics program

Position 2 – Light weight metrics program

Position 3 – Comprehensive metrics program

3.5.2.3 Experiment I. The first decision making issue was about the selection of a software metrics program in a large scale organization. The twenty-four stakeholders exchanged 220 arguments over a period of one week. After the argumentation process, the framework was applied to the argumentation tree. The stakeholders' opinions were computed for the three positions. The accumulated data was normalized using the min-max normalization method. The K-means clustering algorithm was run on the data for four clusters. The framework produced four polarization groups, which are presented in Table 3.3.

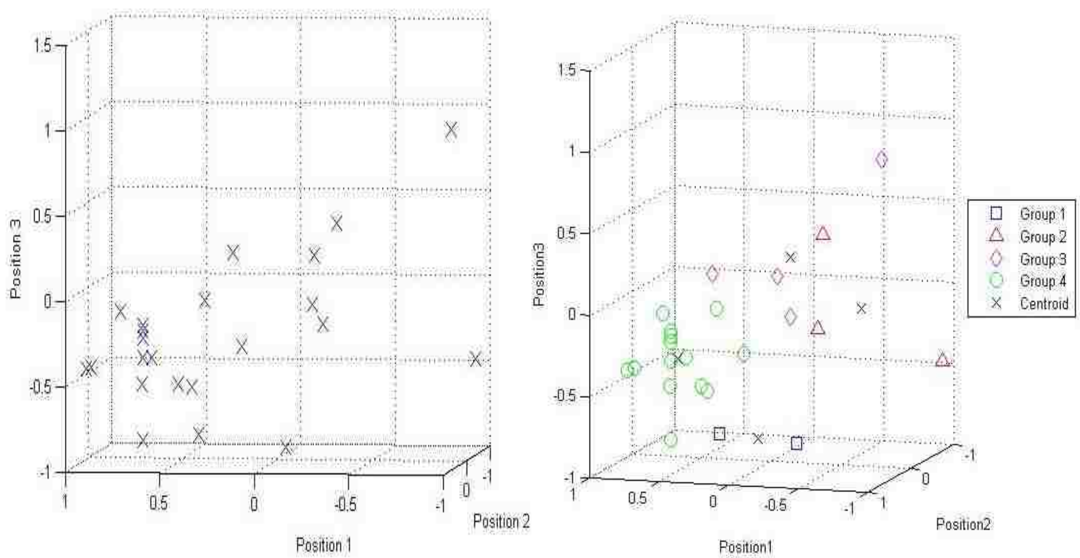
3.5.2.3.1 Polarization groups. The clusters produced by the framework represent polarization groups. The centroid of a cluster represents the opinion of polarization group. Positive values in vector signify the support and negative value represents attack for a position. Figure 3.5a presents the data instances plotted in 3-dimensioinal space. These data instances are the opinion vectors of the stakeholders from the first decision making issue. Figure 3.5b illustrates the four groups produced by the framework. Each polarization group is represented by a different color and a symbol. As there are three positions for the given decision making issue, the vector consists of three elements.

Hence, the framework produced a three dimensional figure. Each axis refers to a position.

Group 1 consisted of two stakeholders. The opinion of group 1 is represented by the vector (0.246, -0.496, -0.941). This signifies that the stakeholders in this group weakly supported position 1 and attacked position 2 and position 3. Group 1 stakeholders strongly attacked position 3. Group 2 consisted of three stakeholders. Group 2 stakeholders not supported any position. Group 3 consisted of four stakeholders who attacked position 1 but they were in favor of position 2 and position 3. Group 4 consisted of fifteen stakeholders who supported position 1 but attacked position 2 and 3.

Table 3.3. Polarization Groups in Experiment I

Polarization groups	Position 1	Position 2	Position 3	Stakeholders
Group 1	0.246	-0.496	-0.941	S8, S9
Group 2	-0.459	-0.605	-0.129	S17, S19, S20
Group 3	-0.349	0.688	0.373	S4, S18, S21, S23
Group 4	0.669	-0.002	-0.402	S1, S2, S3, S5, S6, S7, S10, S11, S12, S13, S14, S15, S16, S22, S24



3.5a. Opinion Vectors before Polarization Assessment, 3.5b. Polarization Groups Produced after Polarization Assessment

3.5.2.3.2 **<u>Group leaders.</u>** Based on the interactions among the stakeholders in polarization groups the relationships among them were derived. There was a tie among the stakeholders in the group 1. Stakeholders S8 and S9 did not interact in their group, and hence one of them was randomly selected as a leader. S19 was the leader of group 2. Because, S19 received highest support from group 2. In polarization group 3, stakeholder S4 or S23 can be selected as a leader. Because, the stakeholders have received negative support from group 3. Table 3.4 presents the relationships of stakeholders in polarization group 4. S2 was the leader in group 4 since S2 received the highest support from his group.

Table 3.4. Stakeholder Relationship Table of Polarization Group 4

Stakeholders	S1	S2	S3	S5	S6	S7	S10	S11	S12	S13	S14	S15	S16	S22	S24
S1	0	0	0	0	0.9	0	0	0	0	0	0	0	0	0	0
S2	0	1	0	-1	0	0	0	0	0	-0.9	0	0	0	0	0
S3	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
S5	0	1	0	2	0	0	0	0	0	0	0	0	0	0	0
S6	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
S7	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
S10	-0.3	0	0	0	0	0	0	0	0	0	0	0	0	-1.6	0
S11	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
S12	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
S13	0	0	0	0	0	0	0	0	0	0	0	0	0	0	-0.6
S14	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
S15	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
S16	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
S22	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
S24	0	0	0	0	-0.4	0	-0.7	0	0	-0.7	0	0	-1.2	0.8	0
Total support received	-0.3	2	0	1	0.5	0	-0.7	0	0	-1.5	0	0	-1.2	-0.8	-0.6

3.5.2.3.3 <u>Discussions.</u> Table 3.5 presents the dissimilarity measurement among the four groups based on their opinion. The opinion of a group and the Euclidean distance (Eq.2) are used to compute the dissimilarity. The information provided by the framework allows decision makers to assess the dissimilarity between the groups. The lower the value between the two groups, the closer they are based on their opinion. As the value between two groups increases they are more likely to be dissimilar. Polarization groups 1 and 4 are close in their opinion but whereas the score between group 1 and 3 is high which signifies that their opinions are dissimilar to a greater extent. Groups 1 and 3 had contrasting opinions. Because, group 1 was in favor of position 1 and they attacked position 2 and position 3. Group 3 however, attacked position 1 but they were in the favor of position 2 and 3.

Table 3.5. Dissimilarity among the Polarization Groups

	Group 1	Group 2	Group 3	Group 4
Group 1	0	1.0808	1.8661	0.8446
Group 2	1.0808	0	1.3913	1.3078
Group 3	1.8661	1.3913	0	1.4536
Group 4	0.8446	1.3078	1.4536	0

Groups 1 and 3 tend to be two different factions in a decision making group. Group 4 was the largest group with 15 stakeholders and they were very close in their opinion with group 1. Group 1 strongly attacked position 3. The decision maker might choose the opinion of group 4 by choosing position 1 as their final decision. Because, this group is largest in terms of number of stakeholders. The decision maker might not consider the opinion of group 2 since they do not support any of the position. He might ask them to come up with a new and appropriate position relevant to the decision making issue. There are several different ways on how the decision maker can use this information. In many cases, when huge participation is taking part in the argumentation system, it would be very difficult to study and analyze each stakeholder's view. Additionally, it is important to know the opinion of every stakeholder.

3.5.2.4 Experiment II. Same set of stakeholders participated in experiment II and exchanged 314 arguments. Stakeholders exchanged arguments for a period of 1 week on the second decision making issue. This experiment dealt with the selection of software metrics program in a medium scale software organization. After the argumentation process, the framework was applied on the tree with K = 4 as input.

3.5.2.4.1 <u>Polarization groups.</u> Figure 3.5a presents the four polarization groups produced by the framework. Group 1 contained fifteen stakeholders. The centroid of the cluster is (0.660, -0.270, 0.564), which signifies that the stakeholders in this group supported position 1 and position 3, and they were not in the favor of position 2. Group 1 and 3 had contrasting opinions. Group 3 consisted of three stakeholders who supported position 2 but attacked position 1 and 3. Group 2 was very close to group 1 in terms of similarity of their opinion. Group 2 however, strongly supported position 1, position 3 and strongly attacked position 2, which is not the case with group 1. The stakeholders in group 4 supported all the three positions, and they strongly supported position 1. Table 3.6 illustrates the polarization group information of experiment II.

Table 3.6. Polarization Groups in Experiment II

Polarization groups	Position 1	Position 2	Position 3	Stakeholders
Group 1	0.660	-0.270	0.564	S1, S2, S3, S5, S6, S7, S10, S11, S12, S13, S14, S15, S22, S23, S24
Group 2	0.853	-0.819	0.939	S9, S16
Group 3	-0.407	0.287	-0.366	S4, S18, S19
Group 4	0.772	0.396	0.302	S8, S17, S20, S21

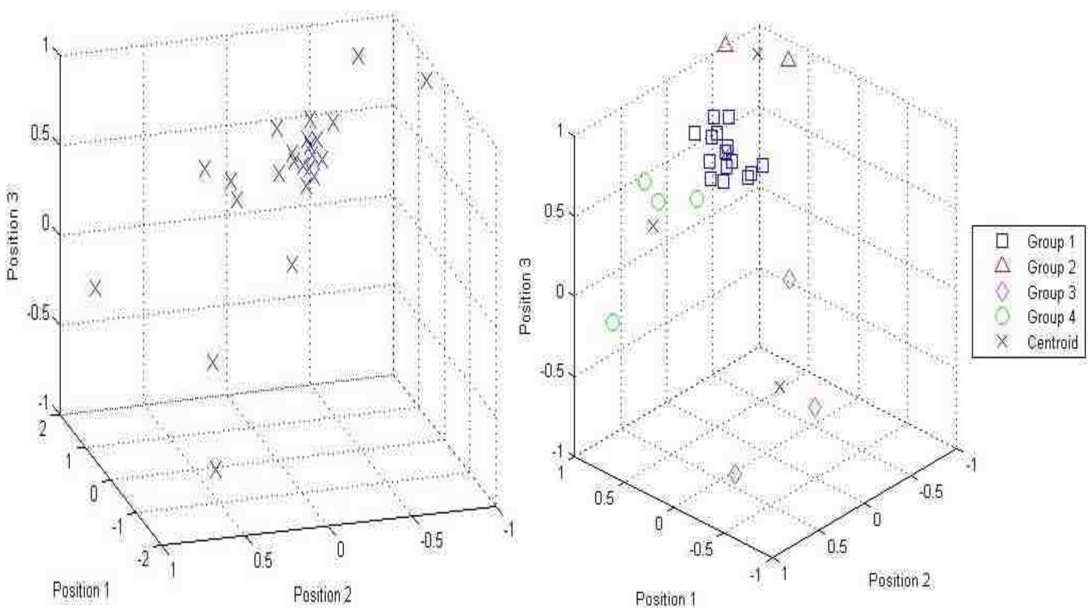


Figure 3.6a. Opinion Vectors before Polarization Assessment, Figure 3.6b. Polarization Groups Produced after Polarization Assessment

3.5.2.4.2 <u>Group leaders.</u> There was a tie among S10 and S14 for the position of group leader in polarization group 1. Because both the stakeholders had received the same strength of support from their own group. Although, the two stakeholders in group 2 shared same opinion they never exchanged any arguments in the argumentation process. We can randomly select either S9 or S16 to be the leader of group. S19 was the leader in polarization group 3, and S21 was the leader in group 4. Table 3.7 presents the relationships of stakeholders in polarization group 4.

Table 3.7. Stakeholder Relationship Table of Polarization Group 4

	S8	S17	S20	S21
S8	-0.7	0	0	0
S17	0	0	0	0
S20	0	-0.1	0.8	0.7
S21	0	0	0	5.2
Total support received	-0.7	-0.1	0.8	5.9

3.5.2.4.3 <u>Discussions.</u> Table 3.8 illustrates the dissimilarity among the polarization groups. Groups 1 and 2 were close in their opinion. Groups 2 and 3 however, were very dissimilar. This valuable information is provided by the framework.

Table 3.8. Dissimilarity among the Polarization Groups

	Group 1	Group 2	Group 3	Group 4
Group 1	0	0.6922	1.5210	0.7243
Group 2	0.6922	0	2.1245	1.3742
Group 3	1.5210	2.1245	0	1.3594
Group 4	0.7243	1.3742	1.3594	0

These tables provide very useful information. This information can be used to understand the social dynamics within the groups. All the tables and figures produced from the polarization assessment give the stakeholders and decision makers an insight into the dynamics. Groups 1 and 2 were close in terms of their opinion and this is clearly evident from Figure 3.6. Group 1 had medium support for position 1 and position 3, group 2 however, had strong support for position 1 and position 3. Group 1 was the largest group with 15 stakeholders. The decision maker might choose the opinion of group 1 as the decision. Because, this was the largest group. As group 1 had contrasting opinion with group 3, the decision maker now has the opportunity to closely deliberate the arguments posted by the group 3 stakeholders. Decision maker can understand why group 3 had contrasting opinion from the largest polarization group.

3.5.2.5 Experiment III. In the last week of our experiment, stakeholders exchanged arguments over the third decision making issue. Stakeholders built an argumentation tree of size 176 arguments over a period of one week. The decision issue in this experiment was about the selection of software metrics program in a small scale organization. After the data was collected, the K-means clustering algorithm has produced four polarization groups. The centroids of groups are presented in Table 3.9.

3.5.2.5.1 <u>Polarization groups.</u> Figure 3.7b presents the four groups produced by the framework. The ten stakeholders in group 1, supported position l, and attacked position 2 and 3. Group 3 was close to group 1 in terms of their opinion. Stakeholders in group 3 however, strongly attacked position 3, but group 1 weakly attacked position 3 and supported position 1 but for the same position group 3 weakly supported. Although their support and attack opinions were similar, the strength of support or attack is varied. Hence they had varied opinion. Groups 2 and 4 had contrasting opinions. The 5 stakeholders in group 2 supported position 2 and attacked other positions. While in the case of group 4, it was the other way round. Group 4 attacked position 2 and supported positions 1 and 3. Group 2 strongly supported position 2 whereas polarization group 4 attacked position 2. As the decision maker knows each and every stakeholder in group 2 and 4, the decision maker can go through the arguments posted by these stakeholders under position 2. After studying those arguments, decision maker can possibly eliminate position 2 from their choice or make appropriate judgment in the context of decision making.

Table 3.9. Polarization Groups in Experiment III

Polarization groups	Position 1	Position 2	Position 3	Stakeholders
Group 1	0.508	-0.380	-0.392	S4, S6, S7, S10, S12, S15, S17, S21, S22, S24
Group 2	-0.266	0.747	-0.663	S8, S14, S18, S19, S20
Group 3	0.088	-0.417	-0.723	S1, S2, S3, S5, S9, S11
Group 4	0.111	-0.627	0.446	S13, S16, S23

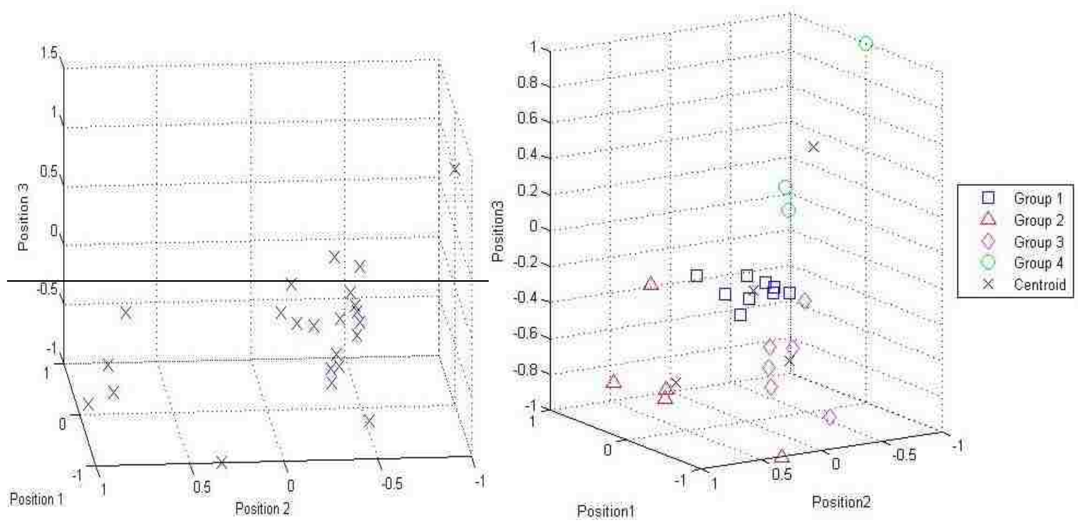


Figure 3.7a. Opinion Vectors before Polarization Assessment, Figure 3.7b. Polarization Groups Produced after Polarization Assessment

3.5.2.5.2 **<u>Group leaders.</u>** Surprisingly, there were very few interactions among the 10 stakeholders in polarization group 1. Although they all have similar opinion, they exchanged very few arguments. Since there were very few interactions among them, not every stakeholder had received support or attack from the rest of the group. There were 8 stakeholders who had not received any argument from the rest of the group. While, the other two stakeholders had received attack from the group. Hence the system randomly picked one among the 8 stakeholders as the leader for that group. Stakeholder S19 was the leader for group 2, S3 was the leader for group 3. The total support received by S13 and S16 were same in group 4. The system randomly selected one of them to be the leader. See Table 3.10 for the stakeholder relationships among the group 2.

Table 3.10. Stakeholder Relationship Table of Group 2

Stakeholders	S8	S14	S18	S19	S20
S8	0	0	0	0	0
S14	0	0.7	0	0.8	0
S18	0	0	0	0	0
S19	0	0	0	0	-0.7
S20	0	0	0	0	-0.9
Total support received	0	0.7	0	0.8	-1.6

3.5.2.5.3 <u>Discussions.</u> Table 3.11 presents the dissimilarity among the polarization groups. Polarization groups 1 and 3 were close in terms of their opinion. See Figure 3.7b and Table 3.11 for more information on dissimilarity between groups. Polarization groups have differences in their opinion. Because, favorability of each group was different for different positions.

Table 3.11. Dissimilarity among the Polarization Groups

	Group 1	Group 2	Group 3	Group 4
Group 1	0	1.3937	0.5360	0.9596
Group 2	1.3937	0	1.2181	1.8055
Group 3	0.5360	1.2181	0	1.1879
Group 4	0.9596	1.8055	1.1879	0

Group 1 is the largest group, three other groups had contrasting opinion with group 1. The decision maker has the opportunity to understand the social dynamics among the groups. All of this information was not available earlier. But, now the decision maker can make more informed decisions using the framework in an argumentation tree.

3.5.3. Decision Support Discussion. The figures, and tables produced by the framework as output are the polarization assessment information. The information provided by this framework is very insightful. It is up to the decision maker on how this information is used. Figures 3.5a, 3.6a, and 3.7a are the machine generated figures before the clustering process. Figures 3.5b, 3.6b, and 3.7b are the machine generated figures after the clustering process is carried out.

Three different experiments were conducted successfully. We realized that the proposed framework for polarization assessment in the argumentation system was effective in identifying the polarization groups and leaders. During the argumentation process, in a few cases, there were few stakeholders who were not in favor of any position. They tend to dislike all of the positions and attack the positions. It is crucial to identify those set of people and help them sort out the problem and satisfy them by either providing new positions or closely deliberating their arguments and interactions. This information would help other users or stakeholders in other groups to share their opinion and understand their goals. In experiment I, polarization group 2 had three stakeholders who did not support any positions. The decision maker might suggest those stakeholders to come up with a new position that might be more appropriate than the three posted positions.

Although stakeholders in a polarization group share similar opinion, some stakeholders might receive attack from rest of the group. This signifies the existence of groups within a polarization group. In many real situations it is important to recognize these sub-groups as well. In the context of this research problem, consider political party A as a group and within a political party there will be several large polarization groups and within those large groups there could be several small polarization groups. This has been observed in several political parties in various countries.

In one of the experiments, stakeholders in a polarization group have not interacted and in this case, the system randomly picks a stakeholder and assigns as polarization group leader. Every stakeholder has an opinion towards a position with varied level of support and attack. This variation in their support might be because of their varied level of expertise for the given problem.

During the analysis of our experimental results, we realized that every stakeholder belongs to every other group with varied level of membership. Polarization groups overlap to a certain degree. The fuzzy based clustering algorithms also seem to be very interesting since these algorithms output the membership of a stakeholder in all the groups. We came across some groups who only share similar opinion and there were no interactions identified among them. Stakeholders S6, S7, S10, S12, S15, S22 and S24 have shared the same opinion across all three experiments in the second empirical evaluation. This is another interesting observation that was recorded in the experimental results. This kind of information was not available earlier.

Earlier some researchers have claimed that, some stakeholders do not present their opinion in the group discussions and argumentation. Because, those stakeholders do not want to give their opinion in public. Due to these reasons some researchers have proposed frameworks that allow stakeholders to participate anonymously. Some researchers have also claimed that if the stakeholders are anonymous in the group discussions, stakeholders seem to be more productive.

There is a wide scope in the selection of a leader from a polarization group. Several leader-selection and leader-election algorithms have been proposed earlier in the area of distributed systems. In case of a tie between two or more stakeholders for the position of group leaders, then we would randomly choose a stakeholder. However, several researchers in the area of distributed systems and others have proposed several different ways to break the symmetry between two agents.

3.6. FINAL REMARKS

Identification of polarization groups and leaders in a Web-based intelligent argumentation system helps in collaborative decision support. The framework presented in this chapter provides polarization assessment information to the decision maker which helps in taking more informed decisions. In addition it also provides feedback to the stakeholders in an argumentation process. We have successfully carried out three different experiments. The experimental results show that the framework is effective in polarization assessment.

4. FUZZY POLARIZATION ASSESSMENT

4.1. PROBLEM DESCRIPTION

In chapter 3, the hard polarization assessment framework was presented. The hard polarization assessment framework assumes that, stakeholders are strictly part of a polarization group. Stakeholders however might share opinions with multiple polarization groups to varied degrees. Hence polarization groups may overlap to a certain degree. Quantifying stakeholders' membership in multiple polarization groups is a crucial issue in the argumentation for collaborative decision making, which is not addressed earlier. A novel approach using fuzzy clustering algorithm to address this issue is presented in this chapter [58]. The method is evaluated using data sets produced from the discussions of twenty four stakeholders.

4.2. SIGNIFICANCE OF THE PROBLEM

The method presented in this section is implemented in the intelligent argumentation system to identify both polarization groups and stakeholders' memberships in multiple polarization groups. This proposed method computes the aggregate opinion of a stakeholder over an issue across all alternatives. This method employs the fuzzy c-means clustering algorithm [5] to compare similarities between the opinions of stakeholders using Euclidean distance metric. A decision maker would know to what extent a stakeholder is sharing his/her opinion with all the polarization groups. This information allows a decision maker to better understand the social dynamics among stakeholders. And, thus make much more informed decisions.

The following example explains how the framework works in an intelligent argumentation system. Suppose a financial policy is under discussion in the senate. The policy is of national economic interest. Both senators and policymakers use the intelligent argumentation system for collaborative decision support. These men and women belong to either political party A or political party B. These parties have contrasting opinions when selecting an alternative for the financial policy. Stakeholders in both party A and B honor the decision taken by their respective party leaders on the policy. The stakeholders themselves however, have their own opinions on the policy.

These opinions may be in contrast to the party's interest. Our method can identify these polarization groups, the aggregate opinion of each polarization group in the senate, and the membership of each stakeholder in the identified polarization groups.

Each polarization group has an aggregate opinion. Political party leaders can assess each senator's degree of membership based on his/her opinions. They can also assess the policymakers in the same manner. The decision maker can both analyze and understand the differences between polarization groups in terms of their opinions. Decision makers can also identify the senator with the highest degree of membership in each polarization group. Our method enables the leaders of both party A and party B to analyze not only the social dynamics among the stakeholders in their party but also within the opposition party.

4.3. RELATED WORK

4.3.1. Polarization Research Work. Polarization is a phenomenon in which people tend to form groups based on the similarity of the members' opinions. Sunstein [51] explained the phenomenon of polarization as well as its association with both social cascades and social influence. Flache and Macy [59], present polarization as:

"A population that divides into a small number of factions with high internal consensus and sharp disagreement between them. A perfectly polarized population contains two opposing factions whose members agree on everything with each other and fully disagree on everything with the out-group."

Social influence is one of the reasons stakeholders in a decision making group both polarize and support one another. In his extended research, Latane identified polarization groups as dynamic. They change throughout the discussion process as stakeholders change their opinions that quantify [54]. This dynamic quality was an additional motivation to develop a method that quantifies a stakeholder's membership degree within each polarization group. The dynamic social impact theory states that stakeholders form groups. These groups tend to polarize the stakeholders' opinions.

The strength between social agents in a network also impacts social influence. Flache and Macy [59] have conducted research based on the Granovetter's theory of the strength of weak ties [60]. The strength between social agents plays an important role in the formation of polarization groups. Centola and Macy presented both the strengths and the weaknesses of long ties [61]. Macy et al. [62] investigated the affect of polarization in dynamic networks. They also investigated both the dynamics of influence and the attraction between agents. Macy et al. [62] discovered that the population self-organizes into antagonistic groups in a social group. They claim that social agents are attracted to others within the same group. These agents become influenced by others with similar opinions. They are conditioned by both the strength and the valence of social ties. Social agents within the social network can self-organize into antagonistic factions without either the knowledge or intent of the social agents. Takacs [63] analyzed both the network segregation and the intergroup conflicts in a social group. Dense in-group and scarce out-group relations are known as segregation. Segregation in a social group supports the emergence of conflicts between polarization groups [63]. Simpson et al. [124] focused on the effects of social identity on the formation of coalitions in a social group. From a social science aspect, the importance of this challenge is understood [124]. We are not, however aware of any other existing solutions for computing the degree of stakeholders membership within a polarization group.

Balkanization and dysfunctional argumentation addressed in [64, 65] are related to polarization. We presented a method and implement it to identify polarization groups and compute each stakeholder's degree of membership in all polarization groups automatically. While Klein identifies the importance of polarization problem, his article [65] does not discuss any method of detection of polarization groups and how they are implemented in the Deliberatorium.

The results produced by the proposed method help decision makers and stakeholders as well. Stakeholders would be benefited by finding others who share similar interests and this helps them connect with others. This is often referred to as "Finding their tribes" in the literature [65]. Our framework helps stakeholders in finding their tribes by providing the polarization group information.

4.3.2. Community Detection in Social Networks. Since the advent of social networking sites [66, 67] in early 2000, many researchers have focused on different aspects of social networks. Several scientists have focused on problems such as community detection, information diffusion and more. The research however, on polarization assessment in social networks is inadequate. The community detection problem [68, 69] differs from the polarization assessment problem. Polarization assessment focuses on how agents with similar opinions come together as a faction. Community is essentially, an association between agents.

A group of agents within a network does not need to either share or polarize their opinions to form a community. Zhang et al. [69] presented methods for identifying communities using both the K-means clustering algorithm [3, 70] and the fuzzy c-means clustering algorithm [5]. This approach developed the use of the K-means clustering algorithm to discover the communities on a social network. It also developed the use of the fuzzy c-means clustering algorithm to present each social agent's membership degree in each community that is discovered. Zhang et al. [69] applied their methods on both Zachary's karate club data [71] and the American football team data [72] to identify the communities that were formed in each. Du et al. [73] presented a novel algorithm [73] on the detection of communities in large-scale social networks. Because large-scale social networks have a huge number of social agents, each social agent is associated with several other social agents. Community detection problem is well explained and investigated in social networks. The polarization assessment problem however, is new in the domain of argumentation systems and social networks.

4.3.3. Clustering Algorithms. Because we are unaware of a polarization group's data, we cannot provide any labels for training the data. Hence, classification techniques, such as decision trees and classifiers, used for grouping the given data cannot be used. In this environment, clustering algorithms are more suitable than classification techniques. The K-means clustering algorithm was used earlier [1] to identify polarization groups. However, K-means carries out hard clustering. Because we want to identify polarization groups and also the degree of membership of stakeholders in each polarization group, soft clustering algorithms are more suitable and outputs more information than hard clustering algorithms. Because, the stakeholders in polarization groups overlap, the fuzzy algorithms are more appropriate.

The fuzzy c-means clustering algorithm is employed here to perform clustering. The decision maker is responsible to provide the 'c' value as an input to the algorithm. Decision makers, given the capability in deciding the number of clusters, would have flexibility in looking at multiple scenarios of polarization formation and relationships among polarization groups by running the algorithm on the argumentation tree several times with different 'c' values. For example, if the decision maker thinks, there are tentatively four polarization groups, he can run the framework and analyze the results, at the same time, the decision maker can also see what happens if 'c' is provided as two. Which stakeholders might form in to two groups? Which polarization groups might converge? The flexibility in choosing the 'c' value can help here in this application environment. However, there are several ways of selecting 'c' value in the fuzzy c-means clustering algorithm and K-means clustering algorithm [74]. We believe that the decision maker should use the prior knowledge about his/her decision making group and select 'c' appropriately.

Vimal et al. [75, 76] from their experiments have learnt that Euclidean distance metric exhibits high accuracy when used in K-means or fuzzy c-means clustering algorithm [75, 76]. The datasets in their experiments was generated using the Syndeca software [77]. Also, Euclidean metric is very often used in detecting communities in social networks [78]. Other similarity measurements, such as Pearson Correlation, can also be used for similarity measurement in this research. But they may lead to more complicated clustering algorithms in argumentation polarization analysis.

Clustering algorithms can be broadly classified as exclusive clustering, overlapping clustering, hierarchical clustering and probabilistic clustering algorithms. Exclusive clustering algorithms such as K-means can be used, but they perform hard clustering. Hierarchical clustering would be more appropriate if we wanted to analyze the intra-group polarization assessment. Overlapping clustering techniques based on fuzzy concepts are more appropriate here, since polarization groups overlap by nature.

The probabilistic clustering methods such as Gaussian mixture model, if used for argumentation polarization analysis in our system, would identify membership of stakeholders in polarization groups with probability. However, degree of membership of stakeholders in polarization groups is more desirable in assessing their memberships in argumentation polarization analysis. We would like to see a stakeholders' degree of membership in a polarization group, not the probability of being in a group. Hence, fuzzy based clustering algorithms seem to be more appropriate. Models such as Latent semantic analysis [79], probabilistic latent semantic analysis [80] or the Latent Dirichlet allocation [81] are more appropriate if used in clustering the argument text.

4.4. FRAMEWORK

Stakeholders in a decision making group participate in the argumentation process using the intelligent argumentation system. They build an argumentation tree by exchanging arguments. The argumentation reduction fuzzy inference engine derives each stakeholder's favorability toward a solution alternative. The obtained data is normalized using the min-max normalization technique. This data is represented as a vector and provided as input to the fuzzy c- means clustering algorithm. This algorithm outputs, 'c' polarization groups. The method presented in this section uses clustering algorithms to provide valuable information for decision support. This method is illustrated in Figure 4.2. The following sub-section presents each step in detail.

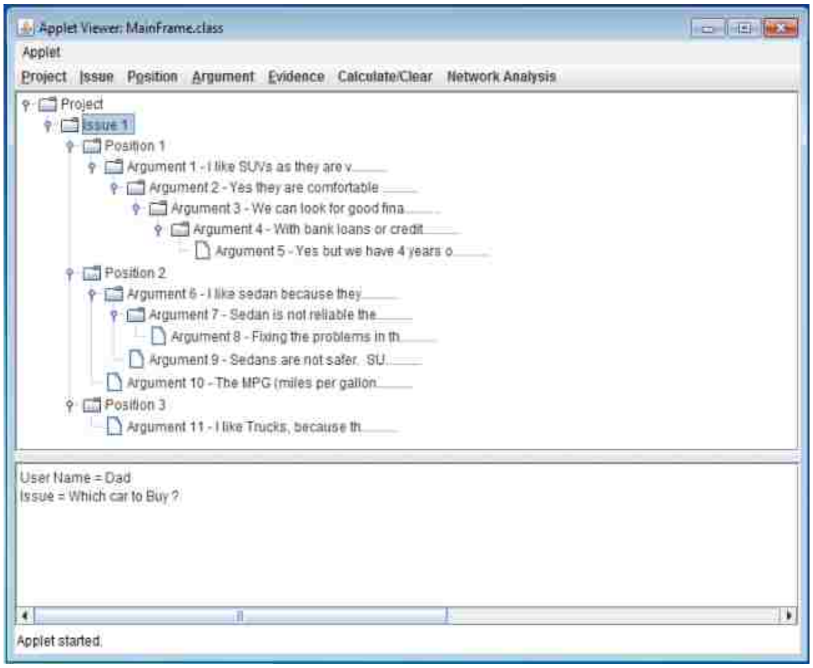


Figure 4.1. Snapshot of Intelligent Argumentation System

4.4.1. Argumentation Process. The exchange of arguments within a decision making group builds an argumentation tree (see Figure 1). Figure 4.3 presents a sample argumentation tree. Figure 4.3 illustrates both a decision making issue (root node) and three positions i.e., alternatives posted under the issue node. Sixteen arguments posted by three different stakeholders are listed under position 1, position 2, and position 3. S1, S2, S3 represent the three participating stakeholders. Arg1, Arg2, Arg3 are the arguments in the sample argumentation tree. Each stakeholder's arguments are represented in a different color.

4.4.2. Data Collection. Our method uses an argumentation reduction fuzzy inference engine to compute a stakeholder's favorability for an alternative. In Figure 4.3, stakeholder S2 has contributed three arguments under position 1. While one argument is directly associated with position 1, and the other two are associated with the arguments posted by stakeholder S1.

The fuzzy inference rules presented in section 2.2.3 are used for argumentation reduction process. The association between (Arg1, position 1) and (Arg4, Arg1) are considered for using the appropriate fuzzy inference rules. Based on the suitable fuzzy rule, the Arg4 is reduced level by level such that it is directly associated to Position 1.

The same procedure was conducted for Arg6. The system ensures that all arguments posted by a stakeholder are directly associated to an argument. The argument based fuzzy inference system reassesses the strengths of the arguments based on the inference rules. The new strength that an argument is assigned is relative to the solution alternative.

Once all arguments are directly associated to the alternatives, the strengths of the arguments posted by a stakeholder under every alternative are aggregated. Hence, the favorability of a stakeholder towards every alternative is derived. This process is conducted for all stakeholders at every position posted in the tree. The favorability of a stakeholder is represented by a numerical value. This value is the sum of the arguments strengths of a stakeholder for a position.

See Figure 4.4 for the argumentation tree after the fuzzy inference process. The favorability of stakeholder S2 for position 1 is the aggregate of the argument's strength: Arg4, Arg2, and Arg6 (see Figure 4.4). Similarly, the favorability of stakeholder S2 for positions 2 and 3 are derived. If the favorability value of a stakeholder for a position is negative, the stakeholder has more attack than support for his/her arguments for that position. If the favorability of a stakeholder for a position is positive, the stakeholder has more support than attack through his arguments.

If the favorability factor of a stakeholder for a position is zero, the stakeholder is neutral in opinion about the position. Because the aggregate of both support and attack of the argument's strengths are neutralized. In another case, stakeholders may not have posted any arguments under that position in the tree. Following the argumentation process, the intelligent argumentation system computes the favorability of each stakeholder for all the positions in argumentation tree.

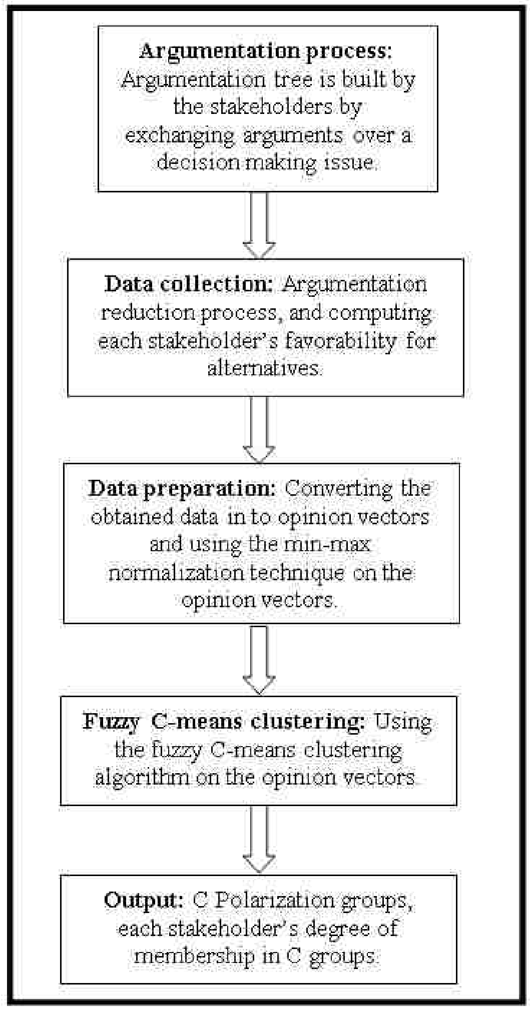


Figure 4.2. Fuzzy Based Polarization Assessment

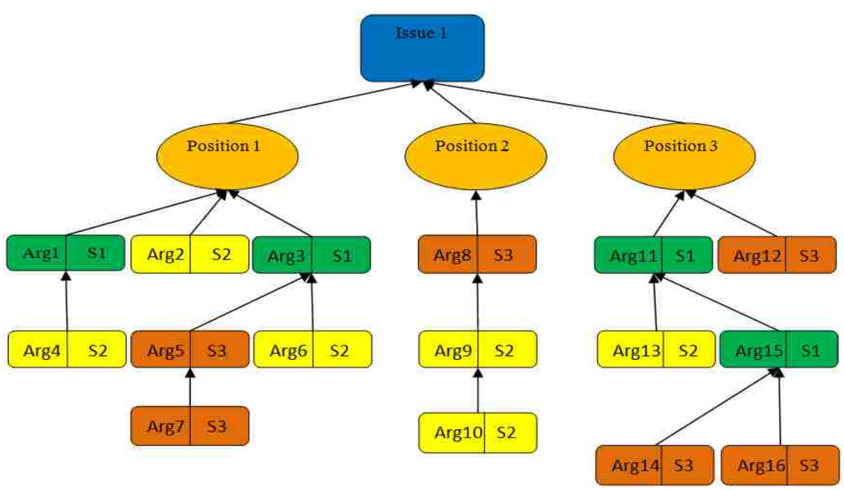


Figure 4.3. Sample Argumentation Tree before Argumentation Inference

All stakeholders are encouraged to participate in the dialog process, but if stakeholders do not present his/her complete opinions on given issues, argumentation polarization analysis might help detect missing opinions since degree of stakeholders in polarization groups from the clustering analysis might be different from their expectations, and prompt stakeholders to address the issue by adding their opinions. Of course, polarization analysis itself cannot solve the problem of missing opinions completely since it is not a problem of argumentation polarization analysis.

4.4.3. Data Preparation. The opinion of a stakeholder is represented as a vector after the favorability of a stakeholder for each alternative is derived. Each element in the vector represents the favorability for a position. The number of positions under an issue in an argumentation tree represents the size of the vector. The vectors are normalized to retain consistency in the data.

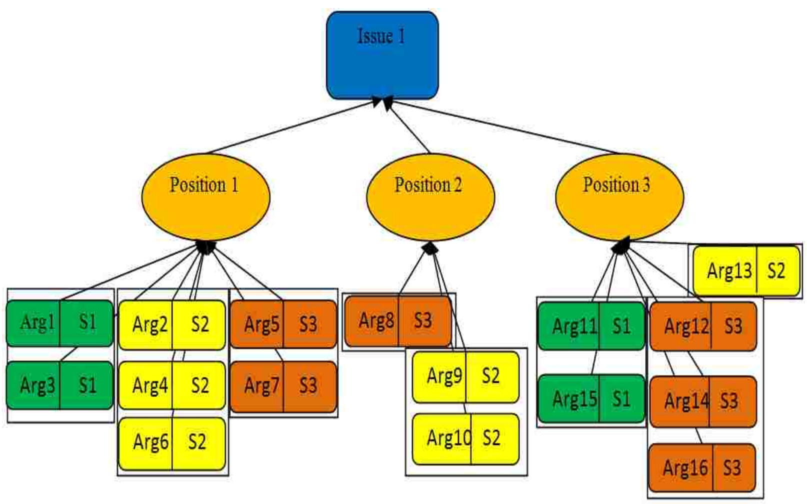


Figure 4.4. Argumentation Tree after Argumentation Inference

The min-max normalization technique (Eq.3) is used to normalize the elements in the vector. We refer to these vectors as opinion vectors. Min A, and max A represent the minimum and the maximum values in the original data respectively. New_min A, new_max A represent the new ranges for the data provided. In our experiments we have assigned new_minA as -1 and new_maxA to +1 as the new ranges. The stakeholder's favorability for an alternative is represented with numerical values ranging from -1 to +1. An element in the opinion vector between -0.1 to -1.0 signifies that the stakeholder attacks an alternative. Values between +0.1 to +1.0 signify that the stakeholder supports an alternative. After the data is normalized, the fuzzy c-means clustering algorithm is used on the opinion vectors.

$$v' = \frac{v - \min A}{\max A - \min A}(new\_\max A - new\_\min A) + new\_\min A \qquad (3)$$

4.4.4. Fuzzy c-Means Clustering Algorithm. This sub-section briefly presents on how the fuzzy c-means clustering algorithm is used in our approach. After the system computes the favorability of each stakeholder across all the positions, the fuzzy c-means algorithm is applied on those favorability vectors. Because each stakeholder's opinion is represented as a vector, we have the opportunity to both compare and assess how close stakeholders' opinions are. Let us suppose stakeholder S_3 is one among the decision making group, and there are three different positions for the decision making issue in the argumentation tree. S_3 has presented his opinion across all three positions. The favorability factor of S_3 is represented as (0.9, -0.2, 0.5). This signals that S_3 is supporting position 1 and position 3 and attacking position 2.

The fuzzy based clustering algorithm outputs the clusters, providing each stakeholder's membership in 'c' clusters. The fuzzy c – means clustering algorithm produces 'c' number of clusters from the given data. The algorithm tries to minimize the objective function over several iterations. When the objective function value remains unchanged, it produces the clusters. The algorithm provides the centroid of each cluster.

Fuzzy c-means clustering algorithm works by assigning each data point to each cluster based on the distance between the cluster center and the data point. The closer the data point is to the cluster center, the higher is its' membership in that cluster. The fuzzy c-means clustering algorithm is based on minimizing its following objective function (Eq. 4).

$$J(F, C) = \sum_{i=1}^{S} \sum_{j=1}^{c} (\mu_{ij})^m (D_{ij})^2 \qquad (4)$$

'S' is the number of data instances, 'C_j' is the centroid of j^{th} cluster, 'F' is the fuzzy membership matrix, 'm' is the weighting factor, 'c' represents the number of clusters, μ_{ij} presents the degree of membership of i^{th} data to j^{th} cluster, D_{ij} is the Euclidean distance between i^{th} data and j^{th} cluster center.

'S' and 'c' are provided as inputs to the algorithm and the algorithm produces membership of each data point in multiple clusters as output.

Algorithm 2. Fuzzy c-Means Clustering Algorithm

Step 1 The algorithm randomly selects 'c' vectors as cluster centers.

Step 2 Calculate the fuzzy membership.

$$\mu_{ij} = 1/\sum_{k=1}^{c} \left(\frac{D_{ij}}{D_{ik}}\right)^{\left(\frac{2}{m}-1\right)}$$

Step 3 Calculate the centroids of the 'c' clusters.

$$C_j = \left(\sum_{i=1}^{S} (\mu_{ij})^m S_i\right) / \left(\sum_{i=1}^{S} (\mu_{ij})^m\right)$$

Step 4 Repeat steps 2 and 3 until the convergence is achieved (The objective function value is minimized).

We used the Euclidean distance metric (Eq. 5) to assess the similarity measurement among stakeholders' opinions in the fuzzy c-means clustering algorithm.

$$D(X,Y) = \sqrt{(X1-Y1)^2 + (X2-Y2)^2 + (X3-Y3)^2} \quad (5)$$

4.4.5. Cluster Analysis of Polarization Groups. The centroid of a cluster is a vector. This vector represents the aggregate opinion of a polarization group. The centroid of each polarization group can be further used to analyze the dissimilarity between polarization groups using the Euclidean distance as a metric. When analyzing polarization groups, we may encounter groups with completely contrasting opinions. In some cases, we might also see groups with similar opinions. Some groups might share similar opinion or contrasting opinion with respect to a particular alternative. These polarization groups tend to form factions, supporting stakeholders within their group. They tend to attack stakeholders in the opposing group, using both their arguments and evidences supporting their arguments. Stakeholders might even use arguments to support their arguments. The advantage of using the fuzzy c-means algorithm is that it provides the membership of a stakeholder in each polarization group. The degree of membership of a stakeholder in a group can help both the decision maker and group leaders understand the loyal stakeholders/followers within his/her polarization group. It also allows for further investigation on new approaches to identify leaders in each polarization group. A stakeholder from each polarization group with highest degree of membership can be acknowledged as the group leader.

In some cases, a stakeholder might absolutely belong to a polarization group. In another instance a stakeholder might have an equal degree of membership in two different polarization groups. This information might help polarization leaders in pursuing each stakeholder based on stakeholders' interest and thereby providing incentives to them. One can also arrange stakeholders in ascending or descending order based on the stakeholders' degree of membership and generate a ranked list. So, each polarization group has a ranked list of stakeholders based on the membership value. The decision maker can also generate top-k list from the ranked list. One could further investigate the overlapping of the ranks of a stakeholder in the multiple polarization groups. A stakeholder might have same rank in two or more polarization groups.

A group of stakeholders participate in the argumentation process using the intelligent argumentation system. After the argumentation process the decision maker or any stakeholder can apply the framework on the argumentation tree for decision support.

4.5. PROCESS OF FUZZY POLARIZATION ASSESSMENT

This section explains the process of the polarization analysis method in the argumentation. Initially a decision maker in an organization posts a decision making issue in the intelligent argumentation system. The decision making stakeholders participate in the argumentation process. Stakeholders exchange arguments over different positions by supporting and attacking different arguments with their own arguments. A stakeholder selects an argument or a position in the argumentation tree and then posts his own argument under the selected argument. Stakeholders are responsible to post the strength of the argument along with their arguments.

Using the intelligent argumentation system, stakeholders build an argumentation tree. Once an argumentation tree is built, the decision maker applies the framework on that argumentation tree by providing the ‘c’ value as an input. The argumentation reduction fuzzy inference system in the framework derives the opinions of the stakeholders. The opinions of stakeholders are generated from the argumentation process. After deriving the opinions, the framework runs the fuzzy c-means clustering algorithm on the opinions using the ‘c’ value provided by the decision maker. The framework then produces ‘c’ polarization groups, and each stakeholder’s degree of membership in all ‘c’ polarization groups.

The decision maker now has the results using which he can know the opinion of each and every stakeholder and their degree of membership in all polarization groups. With the help of the results, stakeholders can now find their tribes and get more connected with them. Figure 4.5 presents an overview of the process of the argumentation polarization analysis and Figure 4.6 presents an interface of the fuzzy c-means clustering algorithm.

Let us suppose we have 35 stakeholders including a decision maker in the decision making group. The decision maker posts a decision making issue and positions pertaining to that issue. These 35 stakeholders participate in the argumentation process using the intelligent argumentation system. After the argumentation process the decision maker runs the framework over the argumentation tree built by these 35 stakeholders by providing the ‘c’ value as an input. The decision maker then analyses the output of the framework (polarization assessment information). The decision maker has the opportunity to study and investigate the results produced by the framework and make more informed decisions.

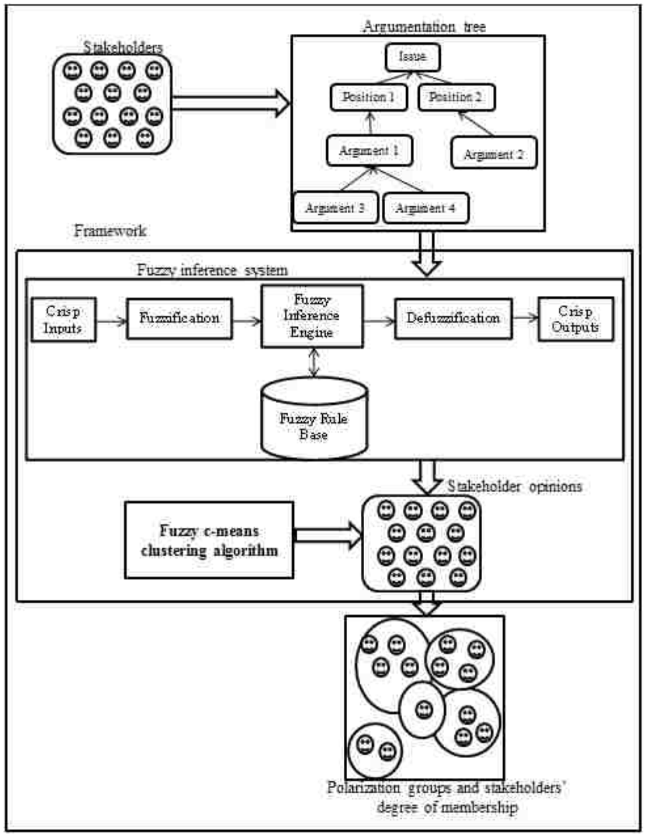


Figure 4.5. Process of Argumentation Polarization Analysis

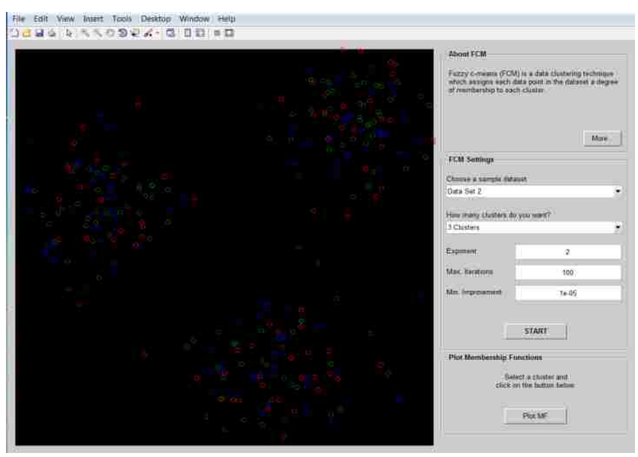


Figure 4.6. A Fuzzy c-Means Clustering Algorithm Interface from Matlab

4.6. EVALUATION

This section presents two different small scale studies carried out at Missouri University of Science and Technology. Results in the first study are validated by the participants. The second study presents three different experiments conducted based on a case study.

4.6.1. Empirical Study 1. In this experiment fourteen students from the e-commerce business class were recruited to participate in our study. The fourteen students played the role of stakeholders and participated by posting arguments in the argumentation tree. The team of fourteen stakeholders were provided with the background case study and the decision making issue to be resolved. After participating for around ten days, an argumentation tree was constructed which consisted of thirty five arguments.

4.6.1.1 Case study. The issue was about the death of Aaron Swartz [56, 57]. Aaron Swartz was an American computer programmer, writer, political organizer and internet activist. He founded the online group demand progress, known for its campaign against the stop online piracy act. Aaron was charged for downloading thousands and millions of articles illegally from JSTOR archive using MIT's open network. If proven guilty, Aaron would face up to thirty five years of prison and a fine up to $1 million. On January 11th, 2013 two years after his arrest, Aaron hanged himself in his apartment.

Issue – What happened with Aaron Swartz? Who is at fault for Aaron Swartz killing himself?

Position 1 – The laws, attorneys and MIT who pushed the case?

Position 2 – Not anybody's fault. It's not the Government's or MIT's fault in anyway. The rules have to be followed in any means.

4.6.1.2 Objective and framework. The objective of this experiment is to evaluate the fuzzy polarization assessment framework with a real world issue. The participating stakeholders were provided with a detailed background about the case and how to use the system. Each stakeholder was provided with a unique username and password to log-on to the intelligent argumentation system to participate in the discussion. Ten days of time was given to the stakeholders to participate in the dialog process. After the discussion process, the fuzzy polarization assessment framework was run on the discussion tree to identify the polarization groups and the membership degree of stakeholders in polarization groups. The results generated by the fuzzy polarization assessment framework were given to the stakeholders to validate.

4.6.1.3 Process and observations. The fourteen stakeholders participated in the discussion process using the intelligent argumentation system which was followed by the application of soft polarization framework on the discussion. C value is provided as two when the framework is used on the argumentation tree. The framework identified two polarization groups and the membership degree of stakeholders in polarization groups after running clustering algorithm for seventeen iterations. Figure 4.7 presents the polarization groups identified by the soft polarization assessment framework.

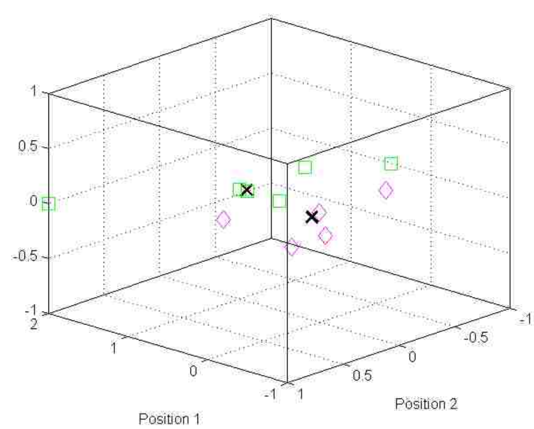


Figure 4.7. Polarization Groups Identified by the Soft Polarization Framework

Table 4.1. Fuzzy Polarization Assessment Results

Polarization group	Position 1	Position 2	Stakeholders
Polarization group 1	0.937	-0.022	S1, S2, S4, S5, S6, S7, S8, S11, S14
Polarization group 2	-0.044	0.096	S3, S9, S10, S12, S13

Table 4.1 presents the polarization groups, opinions of each polarization group and stakeholders in each group. Stakeholders in polarization group 1 strongly supported position 1 and attacked position 2. Stakeholders in polarization group 2 supported position 2 and attacked position 1. Group 1 consists of nine stakeholders and group 2 consists of five stakeholders. The opinions of polarization groups 1 and 2 are contrasting, since they have opposing views on the decision making issue.

The results produced by the framework are presented in Table 4.1. Table 4.2 presents the degree of membership of all participants in the two polarization groups. For example, stakeholder S1 is part of group 1 with a degree of 0.566 and 0.433 with group 2.

Table 4.2. Membership Degrees of Participants in the two Polarization Groups

Stakeholders	Polarization group 1	Polarization group 2
S1	0.566	0.433
S2	0.997	0.002
S3	0.286	0.713
S4	0.614	0.385
S5	0.996	0.003
S6	0.614	0.385
S7	0.827	0.172
S8	0.996	0.003
S9	0.497	0.502
S10	0.158	0.841
S11	0.696	0.303
S12	0.012	0.987
S13	0.102	0.897
S14	0.996	0.003

Table 4.1 and 4.2 were presented to the stakeholders and questions were asked to validate the results. The stakeholders were asked to give their opinion on the results

produced by the system. Out of fourteen stakeholders nine have agreed with the classification (polarization) and degree of membership information produced by the system. Three stakeholders were neutral about the result and two of them disagreed with the result. The plot in Figure 4.8 explains the validation of the results.

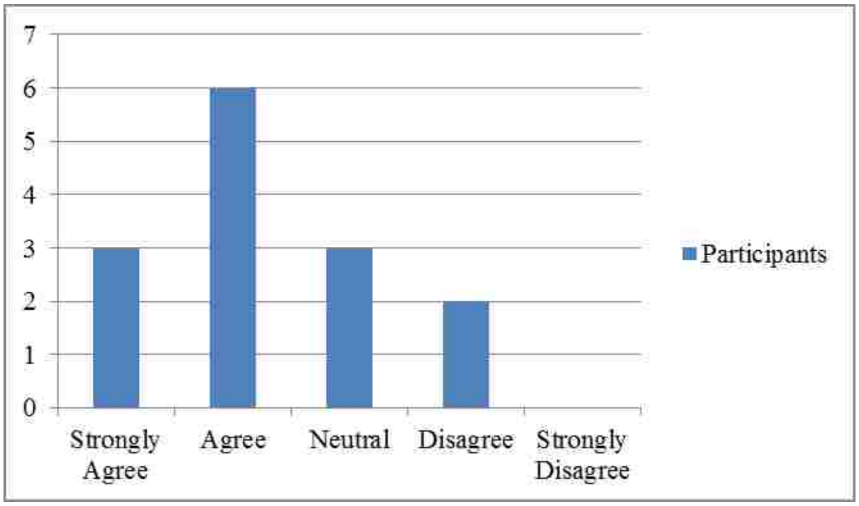


Figure 4.8. Participant's Opinion on the Polarization Assessment Results

4.6.2. Empirical Study 2

4.6.2.1 Background. To evaluate the effectiveness of our proposed framework, we conducted three experiments. Satyavolu [8] conducted an experiment by recruiting twenty-four graduate students from a Software Engineering class at Missouri University of Science and Technology. The dataset in our experiments is from Satyavolu [8].

4.6.2.2 Case study. The decision making issue in the first experiment is about selecting the suitable software metrics program for software development in a large scale organization. The issue in the second experiment is selecting suitable software metrics program for a medium scale organization and for a small scale organization is the third decision issue. Please see article [8] for more information on the case study. The following two examples are the sample arguments from the dataset posted by stakeholders under the first decision making issue. These arguments were posted under the comprehensive metrics program and light weight metrics respectively.

"Since the organization develops mission critical software and software assurance is a major criterion, the most suitable and efficient metrics program would be the comprehensive metrics program as it leads to developing a product of high quality."

"There may be situations where the large organization will have to handle small or medium sized projects. In such situations the organization cannot invest a large portion of its revenue on a comprehensive metrics program. Considering the size of the project and number of employees and deliverables a light-weight metrics program would be best suitable."

Alternatives (Positions)

Position 1 – Comprehensive metrics program

Position 2 – Light weight metrics program

Position 3 – No metrics program

4.6.2.3 Experiment 1. Stakeholders exchanged 204 arguments in one week using the intelligent argumentation system. The proposed method is applied on the argumentation tree with c = 4 as input. The fuzzy c-means algorithm has run for thirty-two iterations by minimizing the objective function score. The framework identified four polarization groups and presented each stakeholder's degree of membership in four polarization groups. After thirty-two iterations, the fuzzy c-means clustering algorithm had stopped and thereby producing the polarization groups as output. Figure 4.9 presents a plot where the objective function values are plotted against the iteration count.

The method has identified four polarization groups and also presented each stakeholder's membership in the four polarization groups. Table 4.3 presents the centroids (opinions) of each polarization group, and stakeholders in each group produced by the method and Table 4.4 presents the membership of each stakeholder in the four polarization groups. The aggregate of the degree of membership of stakeholders in polarization groups is always equal to one.

Group 1 consisted of four stakeholders who attacked comprehensive metrics program, strongly supported light weight metrics program and weakly supported no metrics program. Group 2 consisted of six stakeholders who supported comprehensive metrics program, attacked light weight and no metrics program. The opinions of the polarization group 1 and group 2 were contrasting and they were like two different factions. Group 3 consisted of 10 stakeholders who strongly supported comprehensive metrics program, weakly supported light weight metrics program, and attacked no metrics program. The opinion of the stakeholders in group 3 was contrasting with the opinion of the stakeholders in group 1 and group 2 under different positions. The ten stakeholders in group 3 shared similar opinions with group 2 under the context of comprehensive metrics and no metrics program. They, however, had contrasting opinions under the context of light-weight metrics program. Group 1 stakeholders had similar opinion with stakeholders in group 3 under the context of light weight metrics program. Group 1 and 3 had contrasting opinions with respect to the other two positions. The four stakeholders from group 4 attacked all three alternatives.

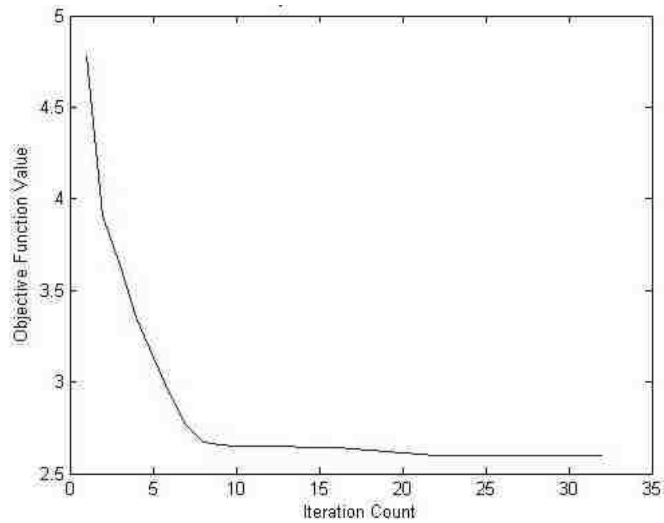


Figure 4.9. Objective Function Values Plotted Against the Iteration Count

Table 4.3. Four Polarization Groups Identified by Framework in Experiment I

Polarization groups	Comprehensive metrics program	Light weight metrics program	No metrics program	Stakeholders
Group 1	-0.3176	0.7687	0.3881	S4, S18, S21, S23
Group 2	0.5022	-0.0841	-0.6036	S6, S7, S8, S12, S14, S24
Group 3	0.7129	0.0220	-0.3222	S1, S2, S3, S5, S10, S11, S13, S15, S16, S22
Group 4	-0.3665	-0.5872	-0.2860	S9, S17, S19, S20

4.6.2.3.1 **Analysis and discussions.** Figure 4.10 presents the opinion vectors of the 24 stakeholders that were plotted in a 3-dimensional co-ordinate system with position 1, position 2 and position 3 as the axis. Position 1, position 2 and position 3 refer to comprehensive metrics program, light weight metrics program and no metrics program respectively in Figures 4.10 and 4.11. Figure 4.11 presents the opinion data of the 24 stakeholders that were plotted after the framework was applied to the collected data. Each polarization group is represented in a different color and a different symbol. These plots also provide more insight on the polarization groups.

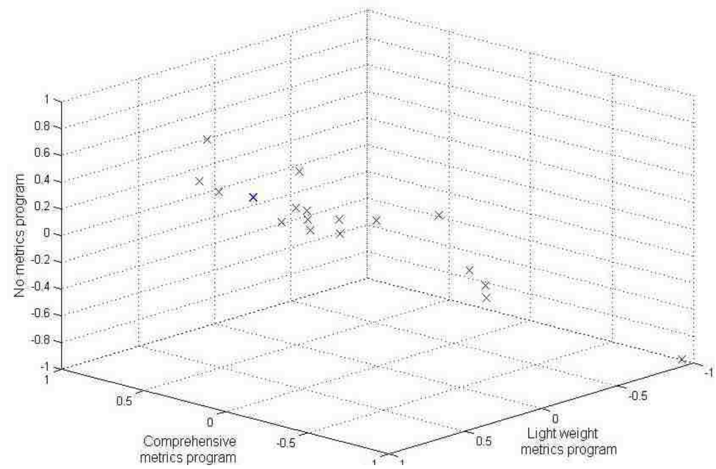


Figure 4.10. Opinion Vectors of Stakeholders Plotted in Three Dimensional space before Polarization Assessment

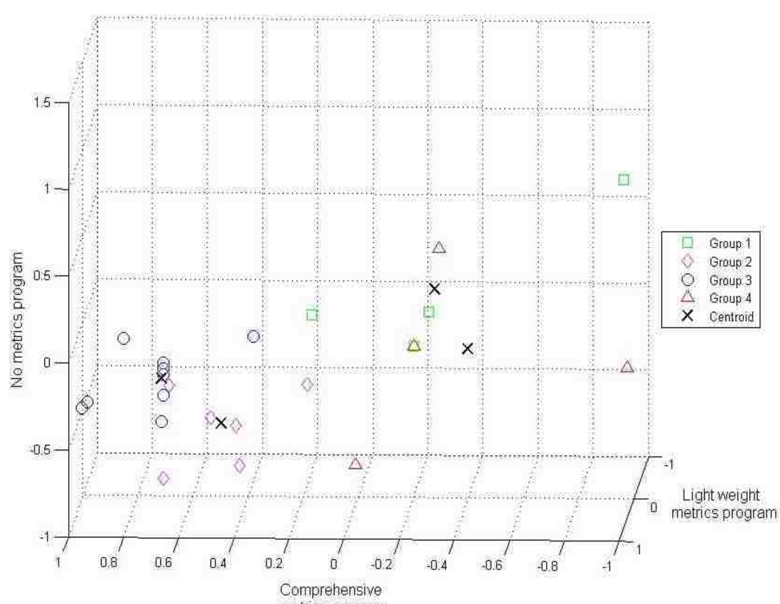


Figure 4.11. Polarization Groups Identified by the Framework in Experiment I

Table 4.4. Each Stakeholder's Degree of Membership in All Four Polarization Groups

Stakeholders	Polarization group 1	Polarization group 2	Polarization group 3	Polarization group 4
S1	0.003718	0.080492	0.910671	0.005118
S2	0.021965	0.261014	0.686536	0.030485
S3	0.00132	0.016425	0.980567	0.001687
S4	0.367586	0.202437	0.188603	0.241374
S5	0.033895	0.263294	0.643013	0.059798
S6	0.010391	0.821822	0.149782	0.018005
S7	0.072309	0.475887	0.323848	0.127956
S8	0.023642	0.742382	0.167901	0.066075
S9	0.064793	0.346609	0.188301	0.400297
S10	0.005732	0.052765	0.934514	0.006989
S11	0.002985	0.031865	0.961423	0.003727
S12	0.028761	0.639512	0.28445	0.047277
S13	0.079695	0.294606	0.532597	0.093102
S14	0.019747	0.479735	0.454579	0.045939
S15	0.012211	0.4535	0.516165	0.018125
S16	0.026053	0.257002	0.684736	0.03221
S17	0.211625	0.153088	0.156209	0.479078
S18	0.642739	0.100943	0.106787	0.149532
S19	0.084737	0.125322	0.096394	0.693547
S20	0.018217	0.049499	0.035057	0.897227
S21	0.975055	0.00813	0.008987	0.007827
S22	0.00132	0.016425	0.980567	0.001687
S23	0.742631	0.087334	0.109836	0.060199
S24	0.001358	0.966495	0.029186	0.002961

Table 4.4 presents degree of membership of the stakeholders in all four polarization groups. For example, stakeholder S9 had a membership of 0.064793 in group 1, 0.346609 in group 2, 0.188301 in group 3 and 0.400297 in group 4. S9 had the

highest membership in group 4 when compared to the degree of membership with other groups. S9 belonged to all the polarization groups however, S9 had highest membership with group 4.

Polarization group 1 and group 2 had contrasting opinions, stakeholders S4, S18, S21, S23 were from group 1 and had contrasting opinion with the stakeholders S6, S7, S8, S12, S14, S24 in group 2. Stakeholder S4 belonged to group 1 and shared opinion with group 1 with a degree of membership of 0.367586, and 0.202437 with group 2. We understand that although S4 is from group 1, shared opinion with group 2 to a degree of 0.202437. Another interesting example from Table 4.4 is stakeholder S14 who shared opinion with group 2 with a degree of 0.479735 and 0.454579 with group 3. The membership values of S14 for group 2 and 3 are very close. Stakeholders from group 3 or the polarization leader from group 3 can possibly pursue S14 to join their polarization group and extend S14s' support. One can also understand that S14 belongs to group 2, however S14 also had a strong affinity for group 3 as well. At the same time stakeholder S24 belongs to group 2, S24 had a membership of 0.966495 in group 2 and 0.001358 in group 1. We can conclude that S24 strongly belonged to group 2 compared to S4 who weakly belongs to group 1 and group 2.

Figure 4.12 presents the membership plot of the twenty-four stakeholders in the decision making group. Every stakeholder has membership values for polarization groups. The highest membership value of a stakeholder among all his/her membership values is presented in Figure 4.12. Some stakeholder such as S3, S10, S11, S21, S22 and S24 strongly belong to a polarization group and they have weak degree of membership with other polarization groups. The rest of the stakeholders have relatively lower membership values in a polarization group, and they actually share opinion and belong to other polarization groups to a good degree of membership.

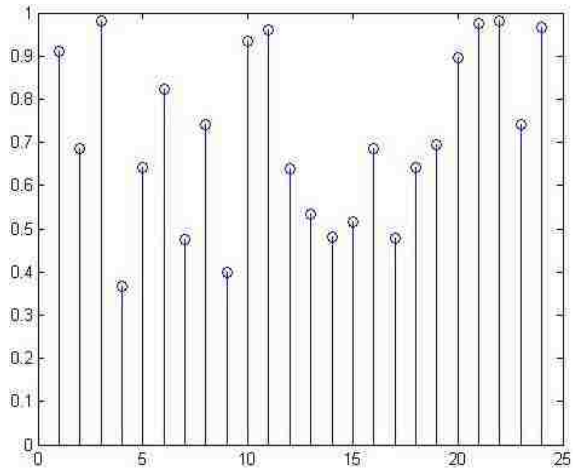


Figure 4.12. Each Stakeholder’s Highest Degree of Membership among all his Memberships in Polarization Groups

Table 4.5 presents the opinion dissimilarity measurement of the polarization groups. Since the centroid of each polarization group is the opinion of that group, the Information from Table 4.5 explains the closeness among the polarization groups in terms of opinion for the given decision making issue. Larger the distance value between polarization groups, more dissimilar the polarization groups are under their opinion for the given decision making issue. For example, stakeholders from group 3 may pursue stakeholders in group 2 and converge to one group. Since group 2 and group 3 are close in terms of their opinion.

Table 4.5. Dissimilarity among the Polarization Groups

	Group 1	Group 2	Group 3	Group 4
Group 1	0	1.5436	1.4574	1.5150
Group 2	1.5436	0	0.3672	1.0529
Group 3	1.4574	0.3672	0	1.2399
Group 4	1.5150	1.0529	1.2399	0

Based on the membership value of a stakeholder in each polarization group, stakeholders are ranked.

Table 4.6. Ranked List of Stakeholders Based on Their Degree of Membership

Polarization group 1	Polarization group 2	Polarization group 3	Polarization group 4
S21	S24	S3	S20
S23	S6	S22	S19
S18	S8	S11	S17
S4	S12	S10	S9
S17	S14	S1	S4
S19	S7	S2	S18
S13	S15	S16	S7
S7	S9	S5	S13
S9	S13	S13	S8
S5	S5	S15	S23
S12	S2	S14	S5
S16	S16	S7	S12
S8	S4	S12	S14
S2	S17	S4	S16
S14	S19	S9	S2
S20	S18	S8	S15
S15	S23	S17	S6
S6	S1	S6	S21
S10	S10	S23	S10
S1	S20	S18	S1
S11	S11	S19	S11
S24	S3	S20	S24
S3	S22	S24	S3
S22	S21	S21	S22

Table 4.6 presents the stakeholders ranked list in the descending order for all the polarization groups. The ranked list is arranged from top to bottom in the descending order. Stakeholder S21 in polarization group 1 had the highest membership value in group 1, and S22 had the lowest membership value in group 1.

Stakeholder S21 is ranked number one in polarization group 1 however S21 is ranked last in group 2 and group 3. A decision maker can correlate the opinion of each polarization group and the ranked list presented in Table 4.6 for more information on social dynamics in the decision making group. By further analyzing the information from Table 4.6, one can generate the top – k list of stakeholders from each polarization group based on the degree of membership. This information can be used to identify the top-k stakeholders who have the highest degree of membership with each polarization group. K value is assumed as four, since c is four. Although there is no association between the variables c and k, we could also generate the top – 6 stakeholders from each polarization group. The framework can even generate the bottom k stakeholders from each polarization group. One can even use the information from Table 4.7 for identifying the polarization leader in each group. A polarization group leader is a stakeholder from a polarization group who leads a group. We could assign stakeholder with highest degree of membership as a leader of that group.

Table 4.7. Top K List of Stakeholders from Each Group Based on Their Rank

Polarization groups	Top K Stakeholders in the group
Polarization group 1	S21, S23, S18, S4
Polarization group 2	S24, S6, S8, S12
Polarization group 3	S3, S22, S11, S10
Polarization group 4	S20, S19, S17, S9

We could further analyze the information from Table 4.6 and Table 4.7 and check for the overlapping or rankings of a stakeholder in multiple polarization groups. For example from Table 4.6, stakeholder S16 had a rank of 12 in both polarization groups 1 and 2. Similarly S11 had a rank of 21 in polarization groups 1, 2, 4 and S21 had a rank of 24 in group 2 and 3.

The information provided by this method offers a great insight in to the social dynamics of the decision making group. The four stakeholders in the polarization group 4 from experiment I do not support any position provided to them. The decision maker might use this information and request those stakeholders to come up with a new position that they think might be more suitable to the given decision making issue. The six stakeholders in group 2 and ten stakeholders in group 3 share similar opinion with respect to comprehensive metrics program. Since majority of the stakeholders support this alternative, the decision maker might choose to make the decision based on this. From Figure 4.12 the decision maker can understand and identify stakeholders who have high and low degree of memberships. The decision maker might possibly also look in and understand to which stakeholder can be pursued more comfortably in case they had to purse stakeholders during the decision making process. The information produced by the approach which is presented in Table 4.3, Table 4.4, Table 4.5, Table 4.6, Table 4.7, Figure 4.10, Figure 4.11 and Figure 4.12 can help decision makers and stakeholders to take more informed decisions.

4.6.2.4 Experiment 2. Selecting the suitable software metrics program for software development in a medium scale organization is the second decision issue. Stakeholders exchanged 314 arguments in the second week on the second issue of experiment using the intelligent argumentation system. The framework was then applied on the tree with c = 4 as input. The framework produced output after the objective function in fuzzy c-means algorithm stabilized after twenty-one iterations. Figure 4.13 shows the objective function value plotted against the iteration count.

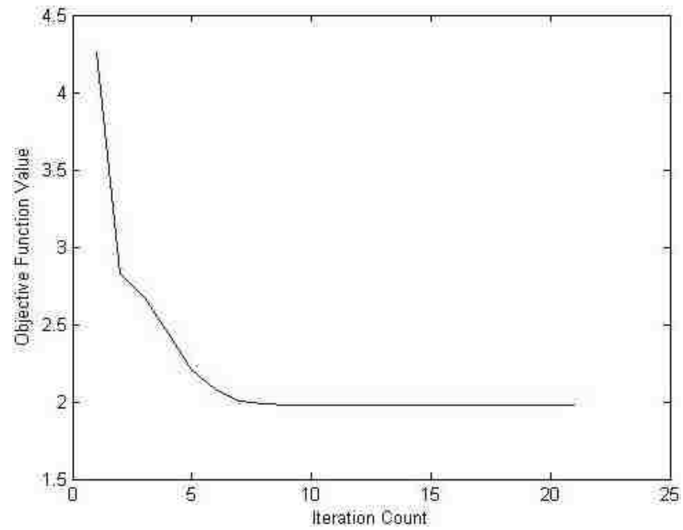


Figure 4.13. Objective Function Values Plotted Against the Iteration Count

Table 4.8. Polarization Groups Identified by the Method from Experiment II

Polarization groups	Comprehensive metrics program	Light weight metrics program	No metrics program	Stakeholders
Group 1	0.8387	0.2598	0.3457	S8, S17, S20, S21
Group 2	0.7918	-0.3518	0.6152	S1, S2, S5, S7, S9, S10, S11, S12, S13, S15, S16, S22
Group 3	-0.6207	0.4604	-0.4039	S18, S19
Group 4	0.4352	-0.1981	0.5325	S3, S4, S6, S14, S23, S24

4.6.2.4.1 <u>Analysis and discussions.</u> Opinions of the polarization groups produced by the framework are presented in Table 4.8. The four stakeholders in group 1 strongly supported comprehensive metrics program, weakly supported light weight metrics program, and no metrics program. Polarization groups 2 and 4 shared similar opinions. Group 2 however, strongly supported and group 4 weakly supported comprehensive metrics program. At the same time, group 2 weakly attacked, and group 4 had very weak attack for light weight metrics. Stakeholders in group 3 had a completely contrasting opinion with the opinions of the group 2, and 4. Polarization group 3 supported light weight metrics and attacked comprehensive and no metrics program. Decision makers now have an opportunity for closely investigating the opinion of group 2. Because, group 2 had highest number of stakeholders. A decision maker can understand the similarities between the opinions of group 2 and 4. One might even predict that the polarization groups 2 and 4 may converge at some point. Within the context of argumentation process in a political environment, one might understand that groups 2 and 4 might form a coalition. Stakeholders S18 and S19 in group 3 only supported light weight metrics program. The decision maker might predict the post-decision effects on these stakeholders based on the decision made. Stakeholders in the decision making group can possibly understand the personal incentives or benefits of those two stakeholders in supporting light weight metrics program.

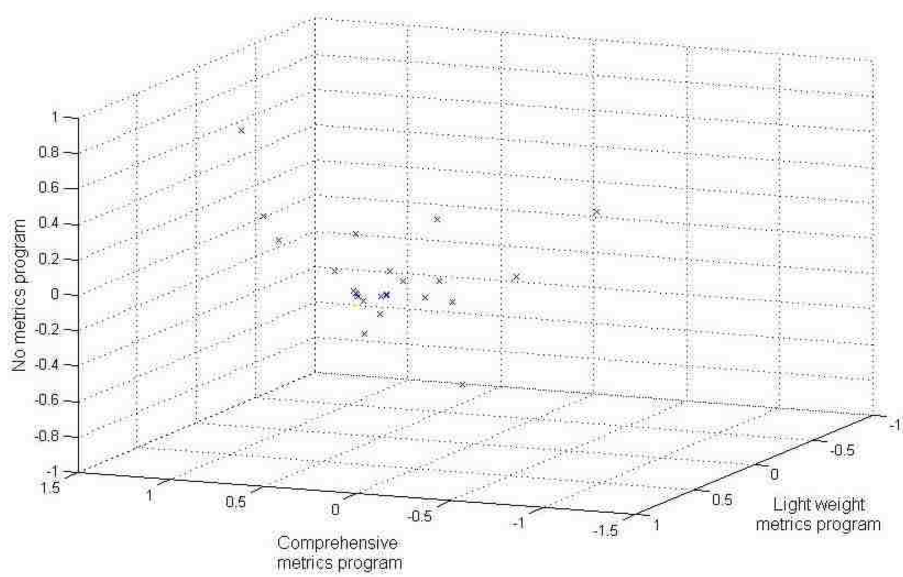


Figure 4.14. Opinion Vectors of Stakeholders Plotted in Three Dimensional Space before Polarization Assessment

Figure 4.14 shows the opinion vectors of the stakeholders plotted in a 3 – dimensional coordinate space. We have three alternatives for the issue and the opinion vector consists of three elements. Each element represents favorability for an alternative. Hence, we have a 3 – dimensional figure. Figure 4.15 shows the four polarization groups that were identified. Each group is represented by a different color and a shape. The x-axis, y-axis, and z-axis represent comprehensive metrics program, light weight metrics program and no metrics program respectively in Figures 4.14 and 4.15. Centroids of the polarization groups are also presented in Figure 4.15. Figure 4.15 is best viewed in color.

Table 4.9 presents degree of membership of stakeholders' in the polarization groups. Table 4.9 helps the decision maker understand the affinity of a stakeholder for each polarization group. Stakeholders S18 and S19 shared similar opinion and they are from polarization group 3 who attacked light weight metrics program. Polarization groups 1, 2 and 4 however, are in favor of light weight metrics program. S18 had a stronger affinity for group 3 over S19 whose degree of membership is lower than S18. Stakeholders in a polarization group share similar opinion however, their affinity for groups might be varying.

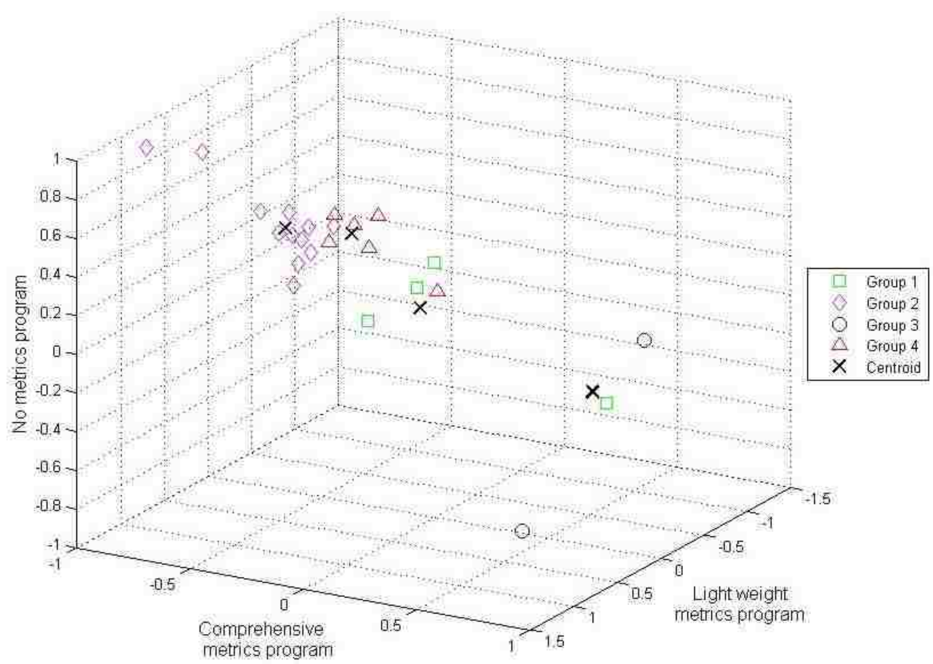


Figure 4.15. Polarization Groups Identified By the Framework in Experiment II

From Table 4.9, we understand that stakeholders from group 4 had strong affinity with their own group. It may be difficult for stakeholders from group 4 to converge with the opinion of group 2.

Table 4.9. Each Stakeholder's Degree of Membership in All Four Polarization Groups

Stakeholders	Group 1	Group 2	Group 3	Group 4
S1	0.066309	0.564548	0.007758	0.361385
S2	0.15174	0.602358	0.014526	0.231377
S3	0.02336	0.077697	0.004414	0.894529
S4	0.176516	0.16427	0.29305	0.366164
S5	0.079482	0.771355	0.007121	0.142042
S6	0.022661	0.066392	0.003128	0.907819
S7	0.035881	0.740234	0.004514	0.219371
S8	0.767019	0.124634	0.013667	0.094681
S9	0.135102	0.513536	0.046085	0.305277
S10	0.024032	0.917903	0.002872	0.055192
S11	0.030108	0.832204	0.003572	0.134115
S12	0.144465	0.64284	0.010414	0.202281
S13	0.023056	0.908369	0.003591	0.064985
S14	0.062764	0.099469	0.006549	0.831218
S15	0.010061	0.966701	0.001044	0.022194
S16	0.132405	0.610679	0.028726	0.22819
S17	0.868031	0.064921	0.009006	0.058041
S18	0.043175	0.034691	0.870638	0.051496
S19	0.16046	0.108674	0.587603	0.143263
S20	0.462958	0.150185	0.02771	0.359147
S21	0.471298	0.153726	0.179534	0.195442
S22	0.004483	0.984292	0.000536	0.01069
S23	0.050795	0.089029	0.012478	0.847698
S24	0.037005	0.108505	0.009782	0.844707

Information from Table 4.9 possibly helps decision makers to predict the mobility of stakeholders within polarization groups. We learn that, even if polarization groups are close or similar in their opinions, groups may not converge on some opinions.

Figure 4.16 presents the highest degree of membership of stakeholders among his/her membership values in all polarization groups. The x-axis presents the stakeholder identification number and the y-axis presents the membership value.

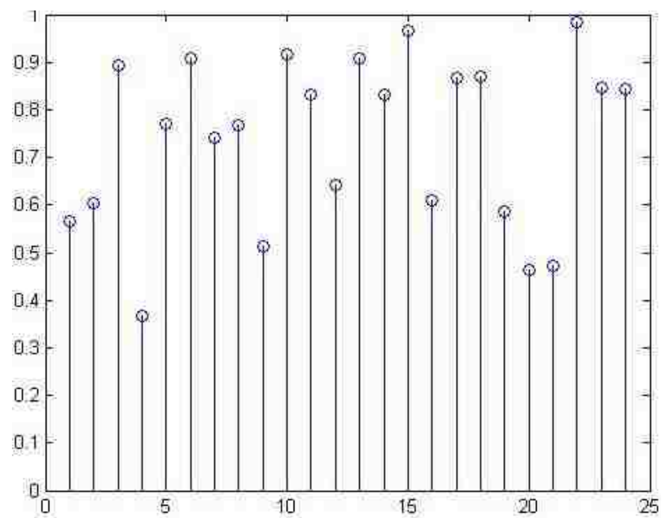


Figure 4.16. Each Stakeholder's Highest Degree of Membership among all his Memberships in Polarization Groups

Table 4.10 illustrates dissimilarity among polarization groups identified in the argumentation process. Smaller distance value between groups signifies groups are closer in their opinion. In the argumentation process stakeholders may change their opinions. The groups identified by the framework are very dynamic by nature. Similarly, distance between the groups change dynamically. Table 4.11 presents stakeholders in each polarization group based on their rank. Ranked lists are generated based on the degree of membership of stakeholders in each group.

Table 4.10. Dissimilarity among the Polarization Groups

	Group 1	Group 2	Group 3	Group 4
Group 1	0	0.6699884	1.6528729	0.6382624
Group 2	0.6699884	0	1.9218194	0.3970221
Group 3	1.6528729	1.9218194	0	1.5573670
Group 4	0.6382624	0.3970221	1.5573670	0

Ranked list is arranged from top to bottom in Table 4.11. Stakeholders S17, S22, S18 and S6 have the highest degree of membership in polarization groups 1, 2, 3 and 4 respectively. S17, S22, S18 and S6 are ranked one in the polarization groups respectively. Stakeholder S22 is ranked last in groups 1, 3 and 4. Because S22's degree of membership in groups 1, 3 and 4 are lowest. Stakeholder S18 has lowest degree of membership in group 2. A decision maker can correlate the opinion of each polarization group and the stakeholders in ranked list and understand the rationale behind stakeholder's degree of membership. A leader from each polarization group can analyze and understand the ranked list and participate in the argumentation process accordingly. Stakeholders with a high degree of membership in a polarization group, usually tend to have low degree of membership in other groups. This is logically sound. Because, the aggregate of membership values of a stakeholder in all the polarization groups is always equal to 1.

Further analyzing information in Table 4.11, one can generate the top – k list and the bottom – k list of stakeholders from each polarization group based on the degree of membership. Table 4.12 presents the top – k list of stakeholders from Table 4.11. Analyzing a ranked list and top – k list of the stakeholders from each polarization group are different possible ways in analyzing the information.

Table 4.11. Ranked List of Stakeholders Based on Their Membership in Each Group

Polarization group 1	Polarization group 2	Polarization group 3	Polarization group 4
S17	S22	S18	S6
S8	S15	S19	S3
S21	S10	S4	S23
S20	S13	S21	S24
S4	S11	S9	S14
S19	S5	S16	S4
S2	S7	S20	S1
S12	S12	S2	S20
S9	S16	S8	S9
S16	S2	S23	S2
S5	S1	S12	S16
S1	S9	S24	S7
S14	S4	S17	S12
S23	S21	S1	S21
S18	S20	S5	S19
S24	S8	S14	S5
S7	S19	S7	S11
S11	S24	S3	S8
S10	S14	S13	S13
S3	S23	S11	S17
S13	S3	S6	S10
S6	S6	S10	S18
S15	S17	S15	S15
S22	S18	S22	S22

Table 4.12. Top K List of Stakeholders from Each Group Based on Their Rank

Polarization groups	Stakeholders
Polarization group 1	S17, S8, S21, S20
Polarization group 2	S22, S15, S10, S13
Polarization group 3	S18, S19, S4, S21
Polarization group 4	S6, S3, S23, S24

From Table 4.11, S12 ranks eighth in polarization group 1 and group 2. Stakeholder S22 ranks least in groups 1, 3 and 4. S22 has same rank in groups 1, 3 and 4. From Table 4.12, one can find S21 ranks third in polarization group 1 and ranks fourth in the third polarization group. So, S21 is in the top k list of the two polarization groups. If one uses Table 4.12 information for polarization leader assessment, then S21 has good chances of being a leader in polarization group 1, group 3 or both.

4.6.2.5 Experiment 3. Selection of a suitable software metrics program for software development in a small scale organization. Same set of stakeholders exchanged 176 arguments in the third week of experiment and constructed an argumentation tree. The framework was then applied on the tree and the framework produced polarization assessment information. C value was provided as four and the system produced four polarization groups. After twenty-three iterations the objective function value in the fuzzy c-means clustering algorithm was stabilized and the four clusters were produced by the system. Figure 4.17 illustrates the objective function values plotted against the iteration count.

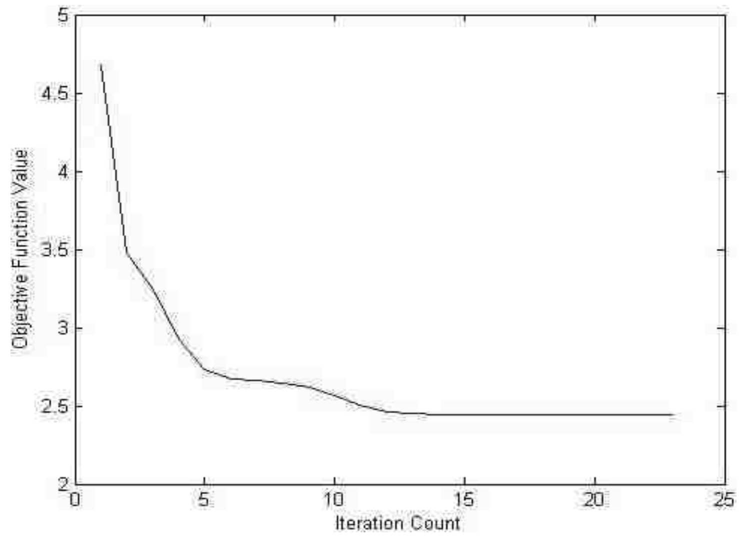


Figure 4.17. Objective Function Values Plotted Against the Iteration Count

Table 4.13 presents both the polarization group information and the stakeholders in each group. The opinion of polarization group 1 and group 2 were similar. Group 1, however weakly supported and group 2 had medium support for the comprehensive metrics program. There were ten stakeholders in group 2 and six in group 1. The three stakeholders in group 3 supported comprehensive metrics program, no metrics program and attacked light weight metrics program. Stakeholders in group 3 and group 4 had completely contrasting opinions. Group 3 stakeholders attacked light weight metrics while group 4 stakeholders strongly supported light weight metrics program. From Table 4.13 one can understand that sixteen stakeholders altogether supported comprehensive metrics program and attacked light weight metrics program and no metrics program. No two groups had shared same opinion with same strength. Because, each individual in a group has unique thoughts and preferences.

Table 4.13. Four Polarization Groups Identified in Experiment III

Groups	Comprehensive metrics program	Light weight metrics program	No metrics program	Stakeholders
Group 1	0.1412	-0.3631	-0.6936	S1, S2, S3, S5, S9, S11
Group 2	0.4859	-0.4062	-0.3973	S4, S6, S7, S10, S12, S15, S17, S21, S22, S24
Group 3	0.1136	-0.5150	0.3081	S13, S16, S23
Group 4	-0.3290	0.8150	-0.6566	S8, S14, S18, S19, S20

4.6.2.5.1 <u>Analysis and discussion.</u> Figure 4.18 presents the opinion of twenty four stakeholders in the three dimensional space, and Figure 4.19 presents the four polarization groups that are produced by the framework. Each polarization group is represented by a different color and a symbol. In Figure 4.19, we can clearly identify the four polarization groups that were separated and the centroid of the polarization groups. It is also interesting to see the similarity of the opinion between the stakeholders rather than just looking in to the similarity between the groups. Figures 4.18 and 4.19 help us in understanding the social dynamics that exist among the stakeholders and polarization groups. From Figure 4.18, one can identify that data instances in some areas are denser than others.

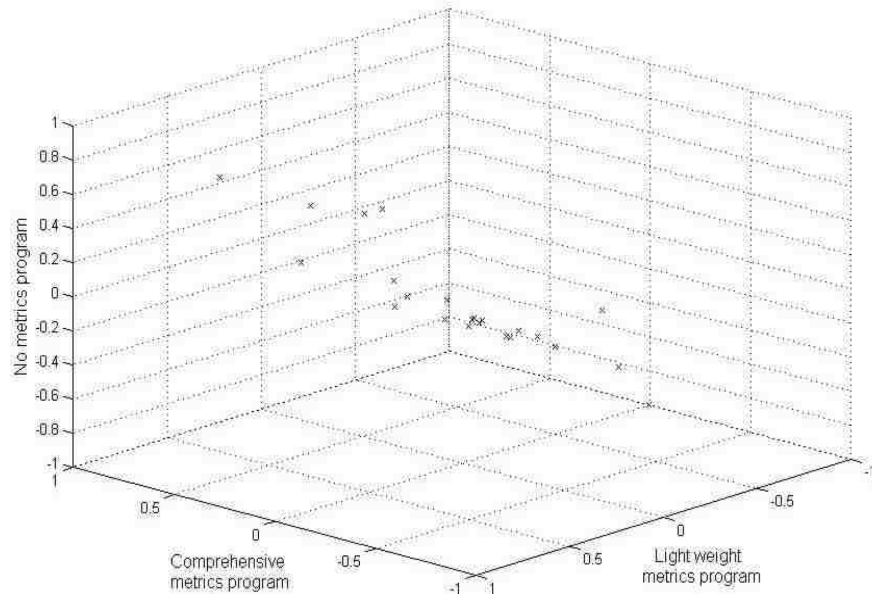


Figure 4.18. Opinion Vectors Plotted in Three Dimensional Space before Polarization Assessment

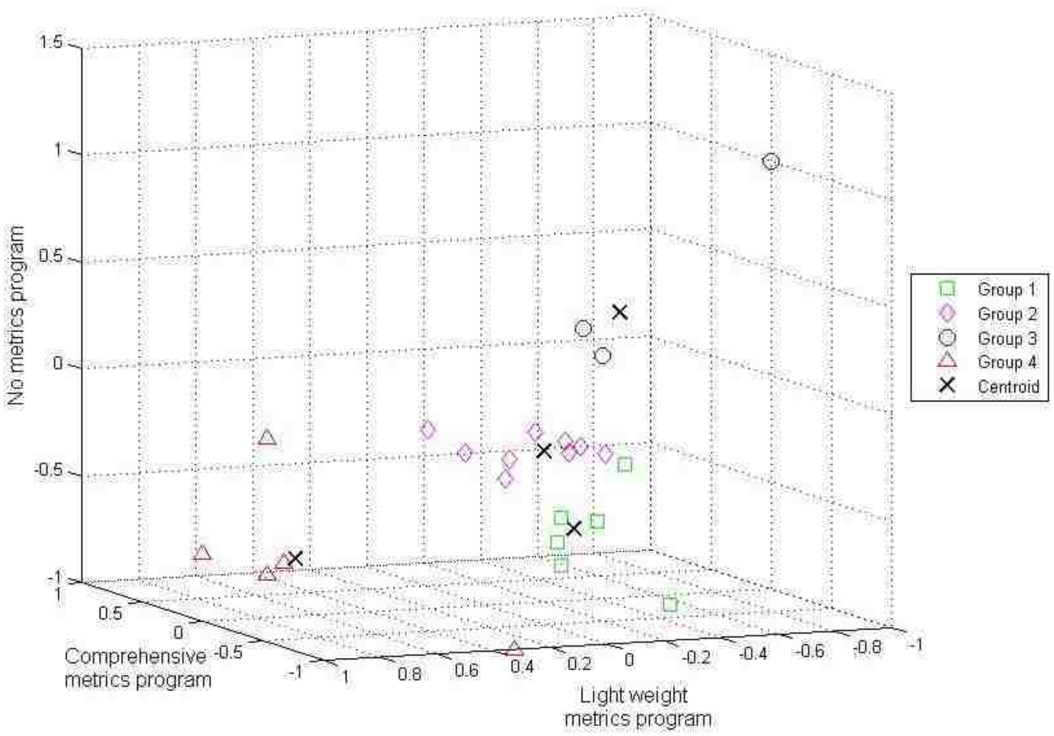


Figure 4.19. Polarization Groups Identified by the Framework in Experiment III

Table 4.14. Each Stakeholder's Degree of Membership in All Four Polarization Groups

Stakeholders	Group 1	Group 2	Group 3	Group 4
S1	0.528969	0.282258	0.149189	0.039585
S2	0.820777	0.13061	0.026625	0.021988
S3	0.840177	0.126731	0.019501	0.013591
S4	0.058591	0.91423	0.021974	0.005205
S5	0.871446	0.083482	0.028168	0.016903
S6	0.209016	0.595462	0.133559	0.061963
S7	0.19047	0.7492	0.047927	0.012403
S8	0.14994	0.144968	0.123818	0.581274
S9	0.616079	0.188771	0.099032	0.096118
S10	0.309594	0.585871	0.085458	0.019076
S11	0.721712	0.240129	0.024678	0.013481
S12	0.152758	0.727372	0.091889	0.027982
S13	0.135651	0.176181	0.615575	0.072593
S14	0.209014	0.19013	0.101489	0.499367
S15	0.058403	0.908283	0.026544	0.00677
S16	0.08337	0.183783	0.712917	0.01993
S17	0.22567	0.658491	0.078144	0.037695
S18	0.030519	0.022795	0.019103	0.927583
S19	0.224934	0.135551	0.115132	0.524382
S20	0.001341	0.00098	0.000742	0.996936
S21	0.376506	0.493723	0.0908	0.038971
S22	0.058591	0.91423	0.021974	0.005205
S23	0.028017	0.04174	0.919501	0.010742
S24	0.138118	0.819122	0.029215	0.013546

Table 4.14 presents degree of membership of the twenty-four stakeholders in each polarization group. The membership of each stakeholder from experiment to experiment was different and this completely depends on the opinion of a stakeholder. In addition, as

stakeholders interact in the dialogue process, stakeholders might change their opinions. Hence their degree of membership in each polarization group changes dynamically. Figure 4.20 illustrates the highest degree of membership value of each stakeholder among all the membership values a stakeholder has with each polarization group. The x-axis in Figure 4.20 presents the stakeholder identification number and y-axis represents the membership value from 0 to 1. In the first experiment we realized that there were more number of stakeholders who were having membership to a polarization group with a value greater than 0.9. The number of stakeholders with a membership value greater than 0.9 has come down from experiment 2 to experiment 3. This is one of the important observations that were recorded from our experiments.

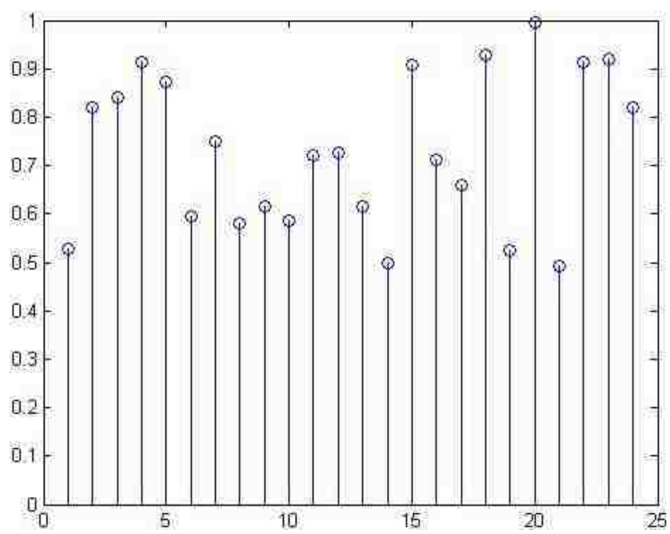


Figure 4.20. Each Stakeholder's Highest Degree of Membership among all his Memberships in Polarization Groups

Table 4.15 presents the opinion dissimilarity measurement among the polarization groups. Polarization groups 1 and 2 are close in terms of their opinion. In fact, the dissimilarity score between these two polarization groups was lowest of all in Table 4.15. The distance between the opinion of polarization group 3 and 4 was the highest in the table, the higher the value is the more dissimilar are the groups in terms of their opinion.

Table 4.15. Dissimilarity among the Polarization Groups

	Group 1	Group 2	Group 3	Group 4
Group 1	0	0.4565845	1.0135276	1.2690062
Group 2	0.4565845	0	0.8050055	1.4908481
Group 3	1.0135276	0.8050055	0	1.7015995
Group 4	1.2690062	1.4908481	1.7015995	0

Based on the membership value of a stakeholder in each polarization group, stakeholders are ranked in Table 4.16. Ranked list is arranged from top to bottom in the descending order. Stakeholder S5 has the highest degree of membership and S20 has lowest degree of membership in polarization group 1.

By further analyzing the information from Table 4.16, the system generates the top – k list of stakeholders from each polarization group based on the degree of membership. This information can be used to identify the top – k stakeholders who have the highest degree of membership with each polarization group. In this experiment, the stakeholders in the top k list are unique. A stakeholder in one list (Top – k list) is not present in another list. See Table 4.17.

Table 4.16. Ranked List of Stakeholders Based on Their Degree of Membership

Polarization group 1	Polarization group 2	Polarization group 3	Polarization group 4
S5	S4	S23	S20
S3	S22	S16	S18
S2	S15	S13	S8
S11	S24	S1	S19
S9	S7	S6	S14
S1	S12	S8	S9
S21	S17	S19	S13
S10	S6	S14	S6
S17	S10	S9	S1
S19	S21	S12	S21
S6	S1	S21	S17
S14	S11	S10	S12
S7	S14	S17	S2
S12	S9	S7	S16
S8	S16	S24	S10
S24	S13	S5	S5
S13	S8	S2	S3
S16	S19	S15	S24
S4	S2	S11	S11
S22	S3	S4	S7
S15	S5	S22	S23
S18	S23	S3	S15
S23	S18	S18	S4
S20	S20	S20	S22

Table 4.17. Top K List of Stakeholders Based on the Ranks in Each Polarization Group

Polarization groups	Stakeholders
Polarization group 1	S5, S3, S2, S11
Polarization group 2	S4, S22, S15, S24
Polarization group 3	S23, S16, S13, S1
Polarization group 4	S20, S18, S8, S19

4.7. FINAL REMARKS

Clearly from the experiments we have realized that the method that is proposed in this chapter has provided more information than the framework [1] that was proposed earlier. This framework has provided the membership of each stakeholder in every polarization group. Also the system provides a stakeholders' highest membership value among all the membership values (in group), this explains the degree of overlap of a stakeholder's participation in other groups as well. The membership value of a stakeholder in the method proposed earlier [1] is either 0 or 1, however in this method the membership ranges from 0 to 1. The objective behind conducting these experiments is to evaluate the effectiveness of the proposed framework.

5. ASSESSMENT OF INDIVIDUAL THOUGHTS BY COLLECTIVE THOUGHTS

5.1. PROBLEM DESCRIPTION

Individual stakeholders express their viewpoints and opinions in their arguments; however opinion of the group i.e. the aggregate thought of group on that argument should be fully analyzed and understood before a decision is made in a collaborative decision making process. Some arguments might be controversial and others might be not trustworthy. They may receive many supporting or attacking arguments. Computing the collective thoughts on arguments and identifying groups of those arguments which are highly agreed or attacked collectively is crucial in the collaborative decision making process. The collective thought of a group on an individuals' opinions convey more information and presents collective assessment of that argument from the group's perspective.

A novel approach is developed to derive collective determination of an argument based on total support and attack that an argument receives in the argumentation tree. The collective determination value and the strength of an argument are used to analyze the relationship between aggregate thought and individual thought of arguments and cluster the arguments. The decision maker will be able to review clusters of arguments with opposing collective thoughts or supporting collective thoughts versus their individual thoughts. Experiment is conducted to evaluate the proposed method, and the experimental results show that the proposed method is effective.

5.2. SIGNIFICANCE OF THE PROBLEM

Every argument posted by a stakeholder carries strength which is provided explicitly by the stakeholder. Stakeholders can also post evidences supporting their arguments in the argumentation process. As the stakeholders attach more evidences supporting their arguments, the strength of the arguments will increase. If an argument is being supported by several other arguments and evidences, it strengthens the argument. In practice, when an argument is posted by an individual, others tend to assess the argument by supporting and attacking based on their views. It is difficult to assess impact of an argument at low level in the tree on the argument which is at upper level in the tree. Hence our method uses argument reduction fuzzy inference engine and computes impact of all the arguments that are connected directly and indirectly to an argument. Although aggregate thoughts on solution alternatives can be computed and the most favorable solution alternative can be identified in the current system, a method needs to be devised to compute aggregate thoughts on individual arguments. Understanding relationships between individual opinions and collective opinions of arguments is important. This helps decision maker to make sound decisions.

The proposed method derives the collective determination value of an argument node by aggregating the total support and the total attack of all its descendant argument nodes that are directly and indirectly associated. The collective determination represents the summation of total support and total attack an argument receives from the rest of the group. Although, the approach computes the collective determination values of all the arguments, it is more important to analyze and understand relationships between aggregate thoughts and individual thoughts on the arguments. Therefore, we cluster the arguments based on relationships between the collective determination and strength of an argument employing the K-means clustering algorithm. The centroids produced for each cluster by the K-means clustering algorithm are further used to analyze the cluster of arguments that are supported and opposed by the collective opinions. The information from the clusters of arguments might possibly provide the decision maker to deliberate these arguments against various alternative solutions.

The analytic results on collective thoughts on arguments and relationships between individual opinions and collective opinions help decision makers to understand aggregate thoughts in a collaborative decision making process and allow participants to see what others think about their opinions.

5.3. RELATED WORK

According to Gilbert [82], “Collective action is interpreted as a matter of people doing something together, and it is assumed that this involves their having a collective intention to do that thing together”. The theory of collective action exists in collective decision making, collaborative decision making, and argumentation process. For instance, if stakeholder S1 posts an argument Arg1 supporting alternative A1, and stakeholders S2, S5, S7, attack the Arg1 with their arguments Arg2, Arg3, Arg4 respectively. Meanwhile, stakeholder S8 joins S2, S5, S7 and attacks Arg1 by supporting Arg4 by posting Arg5. Stakeholders, S2, S5, S7, and S8 are collectively acting upon the argument posted by the stakeholder S1. Argument Arg1 is being collectively assessed by arguments Arg2, Arg3, Arg4 and Arg5. The proposed method derives the collective thoughts of Arg2, Arg3, Arg4 and Arg5 on Arg1. The association between Arg1 and A1 is collectively assessed by Arg2, Arg3, Arg4 and Arg5. Individuals in a social group can also be motivated by providing social incentive in the form of respect, prestige, and other social and psychological objectives [83]. This is another reason to identify arguments with supporting collective thoughts and opposing collective thoughts.

According to Rashotte [84], "Social influence is defined as change in an individual's thoughts, feelings, attitudes, or behaviors that results from interaction with another individual or a group. Social influence is distinct from conformity, power, and authority". Kelman, in 1950s' introduced a theoretical framework for the analysis of social influence in the social groups. Kelman [85, 86] further classified the social influence in to compliance, identification and internalization. In the argumentation system, the social influence occurs through the arguments posted by the individuals. From the dynamic social impact theory of Latane [50], we understand that influence is one of the crucial factors in the group processes. Macy, James and Flache in their article [62], present the research on the dynamics of influence and attraction among the agents in a network. "Formally, social pressure on agent i to adopt a binary states (where s = +1 or -1) is the sum of the states of all other agents j, conditioned by the weight (W_{ij}) of the dyadic tie between I and j ($-1.0<W_{ij}<1.0$)" [62].

$$P_{is} = \frac{\sum_{j=1}^{N} w_{ij} s_j}{N-1}, \; j \neq i \qquad (6)$$

s = +1 or -1, which signifies that the social pressure could be both ways, and it could be for good cause or a bad cause. The intelligent argumentation system is based on the fuzzy systems, where the strength of the argument ranges from [-1, +1]. Since the social pressure in argumentation system is through arguments, we intend to derive the collective thoughts on the arguments.

According to Scheuer et al. [87, 88], discussion assessment drives for improving successful knowledge sharing, resolution of the conflicts among the stakeholders and responsiveness of the participants. There are different ways to find and analyze the credibility of posts in Web-blogs, and discussion forums. Earlier, some researchers suggested to provide user ratings to the posts based on which the posts are rated on a scale. There are some discussion forums on the Web, where the posts can be rated by a stakeholder and hence the collective assessment of that post is quantified. However it does not consider the negative rating provided by the stakeholders who may contradict that post. The collective viewpoint on an individual thought may force others to read that post.

The content quality assessment in collaborative systems is a challenging issue, when the contributions made by the stakeholders are in natural language. It is difficult to assess the quality of the contribution; however with the participation of the stakeholders for rating a post, the collaboration tool [88] evaluates the quality of each and individual post at the content level. Scheuer et al. [88] presented an argumentation system in the education domain for students. They presented an approach for assessing the quality of the content in a post. A student rates argument posted by other students and this helps all the participants to understand the quality of a post in the argumentation system [88]. The idea of peers evaluating a post is good, but however not all the stakeholders may be interested in evaluating the post. Few researchers are working in the area of text analytics for argumentation [89, 90, 91, 92]. Text analytics to resolve argumentation challenges would be interesting to see.

5.4. METHOD FOR ASSESSING AGGREGATE THOUGHTS ON INDIVIDUAL ARGUMENTS

5.4.1. Deriving Collective Thoughts on an Argument. Figure 5.1 presents the method. Since the collective thoughts on an argument can only be assessed and analyzed collectively by the group, the collective determination value is derived from the arguments posted by the individuals in that group. The total support an argument receives in the argumentation tree is called the collective support and the total attack an argument receives is called the collective attack. The collective determination of an argument is the aggregate of collective support and collective attack.

Collective determination of an argument = (Total collective support of an argument) + (Total collective attack of an argument)

An argument with positive value of collective determination illustrates that the argument has more support than attack from the collective thoughts. An argument with negative value of collective determination presents that the argument has more attack than support from the collective thoughts of stakeholders through their arguments. In case if an argument has a collective determination value equivalent to zero, this signifies that the aggregate of collective support and collective attack have neutralized the value or the argument has no support or attack from other arguments in a tree. In sub-section 2.2.3, the fuzzy heuristic rules and the fuzzy inference system are used to compute the favorability factor of an alternative. In this section we present a detailed example to show how the fuzzy inference system is used to derive the collective thoughts on an argument. Figure 5.1 presents a sample argumentation tree consisting of an alternative and nine different arguments. The arguments Arg1, Arg5, Arg6, Arg8 and Arg9 in Figure 5.1 are the leaf arguments that are not supported or attacked by other arguments in the tree, the collective determination for these arguments is zero. The collective determination of Arg3 is the strength of Arg5 and the collective determination of Arg7 is the aggregate of strengths of Arg8 and Arg9. In the intelligent argumentation system, the strength of the argument is bound to range from -1 to +1.

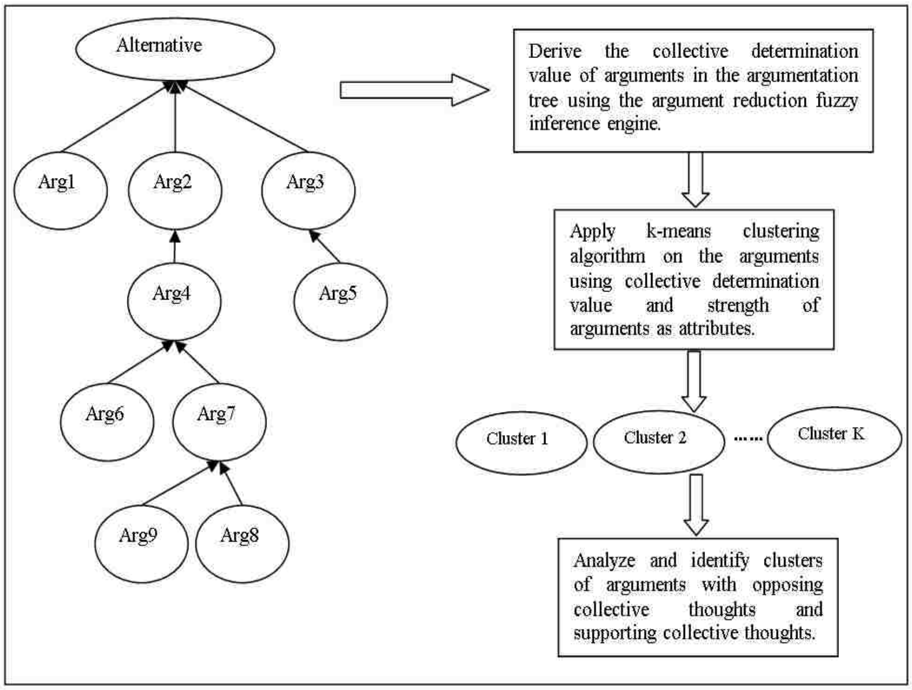


Figure 5.1. Collective Assessment of Arguments and Classification of Arguments Based on Relationships between Individual Opinion and Aggregate Opinions

From Figure 5.2, Arg8 and Arg9 are indirectly associated to Arg4 through Arg7. To compute the collective determination for Arg4, the fuzzy inference system will reduce arguments Arg8 and Arg9 to one level, where Arg8, Arg9 are directly related to Arg4. The strength of arguments Arg7 and Arg8 are provided as inputs to the argument reduction fuzzy inference engine, and inference engine will provide new strength of argument Arg8 which is now directly associated with argument Arg4. The association between Arg7 and Arg4 are considered during the reduction process. Similarly, the strengths of argument Arg7 and Arg9 are also provided as inputs to the argument reduction fuzzy inference engine, and the fuzzy inference engine will produce a new strength of argument Arg9, and now argument Arg9 is directly associated with argument Arg4. All the descendant arguments of Arg4 are child arguments, Arg8, Arg9, Arg6 and Arg7 are directly associated with argument Arg4. To derive the collective determination of argument Arg4, the system aggregates the new strength of arguments Arg8, Arg9 with the strength of argument Arg6 and Arg7. The collective determination is derived for every argument in the argumentation tree. After computing the collective determination value of the arguments, the system normalizes the data using the min-max normalization technique. Eq. (7) is used to normalize the obtained data; we assign new_max A to +1 and new_min A to -1, since we want the new data to be normalized to -1 to +1.

$$v' = \frac{v - \min A}{\max A - \min A}(new\_\max A - new\_\min A) + new\_\min A \qquad (7)$$

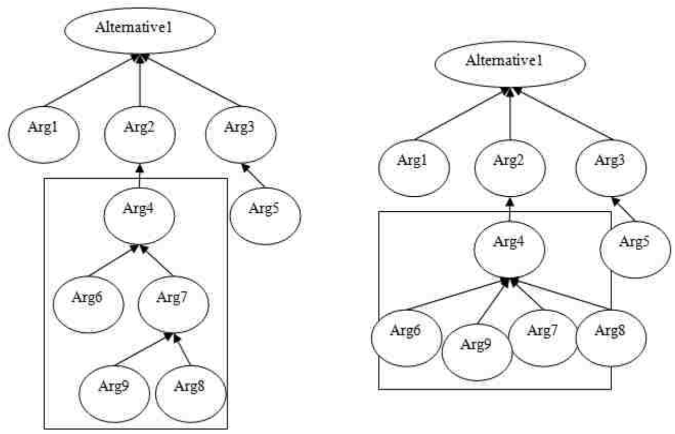


Figure 5.2. Sample Argumentation Tree

5.4.2. Classification of Arguments Based on the Relationship between Individual and Aggregate Thoughts. In this section, we explain how to classify arguments and identify the cluster of arguments with opposing collective thoughts and cluster of arguments with supporting collective thoughts. A stakeholder presents his view point in the argumentation process, and other stakeholders collectively either oppose or support the argument with their thoughts. We are interested in two types of clusters (see Table 5.1),

- Individual view point with opposing collective thoughts – The individual view point represented by an argument is opposed collectively by other stakeholders. In this case, the collective thoughts of the stakeholders oppose the individual argument.
- Individual view point with supporting collective thoughts – The individual view point represented by an argument is supported collectively by other stakeholders. In this case, the collective thoughts of the stakeholders support the individual argument.

Table 5.1. Cluster Labels for Identification of Arguments with Opposing and Supporting Collective Thoughts

Strength of Argument	Collective determination	Cluster labels
-1	-1	Individual view point with
1	-1	opposing collective thoughts
-1	1	Individual view point with
1	1	supporting collective thoughts

The collective determination value and the strength of an argument are the attributes in the K-means clustering algorithm [3]. Each cluster is analyzed by referring the centroid of a cluster. The Euclidean distance metric is used for similarity measurement among the data instances in the K-means clustering algorithm [3].

x = Strength of an argument

y = Collective determination of an argument

$$d(x,y) = \sqrt{(x1 - y1)^2 + (x2 - y2)^2} \tag{8}$$

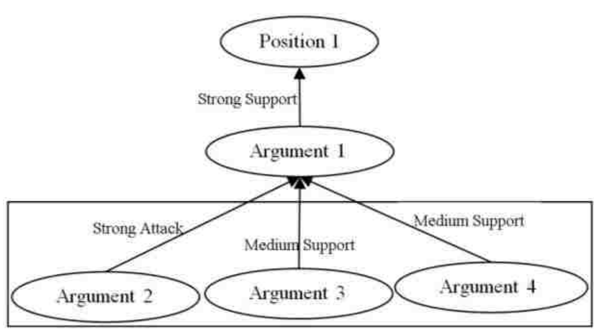


Figure 5.3. After Argumentation Inference Process

Figure 5.3 shows a sample argumentation tree, the relationship between Argument 1 and Position 1 is strong support, which is assessed by the association between Argument 1 and the collective thoughts from Argument 2, Argument 3, and Argument 4.

The clustering algorithm accepts the arguments itself as the input for clustering along with K as the number of clusters. The output of the algorithm is K clusters with the given arguments grouped based on the similarity measurement. The centroid of each cluster represents the cluster. K-means clustering algorithm provides the flexibility to the decision maker in providing the number of clusters required to see in the given argumentation tree data. After running the clustering algorithm over the tree, every argument that is posted will be classified under a cluster. Every cluster centroid has the collective determination of the argument and the strength of an argument. For example, if the centroid of a cluster is (0.9, 1.0), this signifies that the arguments or viewpoints in this cluster are supported by the collective thoughts. There might be several other types of clusters as well. The classes of clusters presented in Table 5.1 can be further classified with several linguistic labels such as strong opposing collective thoughts, weak supporting collective thoughts [93].

5.5. EVALUATION

5.5.1. Background. The dataset in this experiment is from Satyavolu [8]. The decision making issue in this experiment is the selection of software metrics program for a large scale organization. No metrics program, light weight metrics program, and comprehensive metrics program are the three different alternative solutions provided.

5.5.2. Classification of Arguments. The argumentation tree consists of 204 arguments. The argumentation system has computed the collective determination value of all 204 arguments in the tree. The K-means clustering algorithm was run on the data for nine clusters. The cluster centroids are presented in Table 5.2. Figure 5.4 illustrates the nine clusters produced by the K-means clustering algorithm.

The arguments or the individual viewpoints are analyzed after the K-means clustering algorithm has produced the clusters. Cluster 8 contains ten arguments which are supported by the collective thoughts. The four arguments in cluster 7 are also supported by the collective thoughts from the group. The remaining arguments in the argumentation tree are opposed by the collective thoughts.

Table 5.2. Cluster Centroids Produced by the K-means Clustering Algorithm

	Argument strength	Collective determination
Cluster 1	-0.6724	-0.0028
Cluster 2	-0.7500	-0.8814
Cluster 3	-0.8417	-0.0039
Cluster 4	-1.0000	-0.0483
Cluster 5	0.7988	-0.0560
Cluster 6	-0.7571	-0.2532
Cluster 7	-0.2750	0.0203
Cluster 8	0.7900	0.4269
Cluster 9	-0.4600	-0.0300

The ten arguments in cluster 8 are moderately supported by the collective thoughts. The two arguments in cluster 2 are strongly opposed by the collective thoughts, and it might be helpful for the decision makers to overview these arguments. It can provide more insight in to the problem, and get more understanding on why those two arguments were strongly opposed by the collective thoughts. The decision maker can identify the stakeholders behind the opposing or supporting collective thoughts, with added analytical ability the decision maker might also investigate further on the personal incentives or benefits of the stakeholders on opposing those individual viewpoints. Arguments in cluster 1, cluster 3, cluster 4, cluster 5, cluster 6 and cluster 9 are weakly opposed by the collective thoughts. The weight of the arguments in cluster 8 as represented by the centroids is 0.7900 and the collective determination is 0.4269, which signifies that the collective thoughts are supporting only to certain degree. In the best case, possibly a group of arguments could be supported by the collective thoughts with a collective determination of 1. The classes of cluster labels can be further classified based on how strong or how weak the collective thoughts are opposing and supporting. This information could also provide the stakeholders with a good feedback about the arguments they have posted. They could understand the arguments that are in the interest of the group collectively. In several situations, as the argumentation discourse continues, the discussion evolves and the tree grows largely, it is very difficult to keep track of all the arguments, and it is crucial to see the group of arguments that have been supported with collective thoughts.

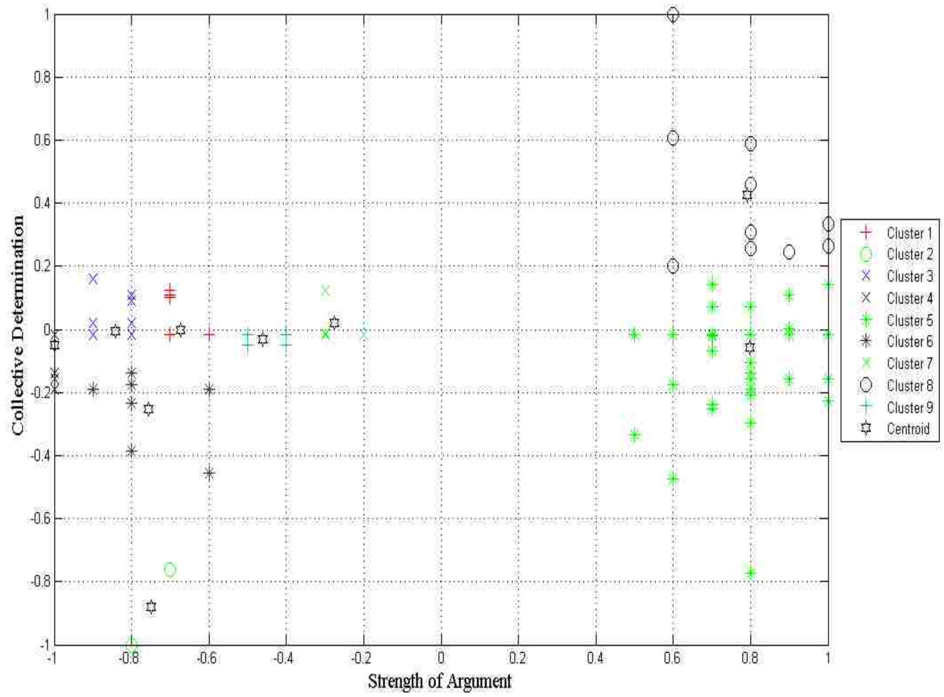


Figure 5.4. Clusters of Arguments (best viewed in color)

Figure 5.4 presents the nine clusters produced by the proposed method, the horizontal axis is the strength of the argument i.e. the individual opinions and the vertical axis is the collective determination i.e. the collective thoughts.

6. IDENTIFYING OUTLIER OPINIONS IN ARGUMENTATION TREE

6.1. PROBLEM DESCRIPTION

In a collaborative dialog process, stakeholders exchange both their views and opinions. The intelligent argumentation system allows a group of stakeholders to post their decision making issues, solution alternatives (positions), and exchange arguments over those alternatives to reach consensus. In the dialog process, as stakeholders exchange arguments, some change their opinions, some strengthen their opinions, and some weaken their opinions [48]. Each stakeholder's opinion within the argumentation process must be considered for collaborative decision support.

Argumentation is an important step in a collaborative decision making group. In the decision making group, stakeholders form communities and polarize on their opinions. Some stakeholders approach the problem very uniquely. Their opinions are further away from either any another stakeholder or polarization group within the opinion dimensionality. Those opinions are referred as the outlier opinions, as they are very different from the individual opinions of the group. According to Hawkins [94], "Outliers are observations which deviate significantly from other observations as to arouse suspicion that these are generated by a different mechanism." In face-to-face discussions, participating stakeholders can understand the social dynamics within their group. Participants with some analytical ability might be able to identify his peers with outlier opinion. Our objective is to incorporate this feature in computer enabled collaborative argumentation systems.

By identifying the outlier opinions, the decision maker can closely investigate the arguments posted by that stakeholder. The decision maker can also encourage discussions on outlier opinions and this can refine the opinions of the stakeholders based on the outlier opinion. More discussions leverage in refining the opinions and building consensus within the group. Both the decision maker and the decision making group are responsible for understanding the underlying semantics of the outlier opinion. For example, if an outlier opinion is not in the interest of the organization and promoting extreme ideology. The decision maker can take relevant action against the owner of that outlier opinion. This problem is new to the argumentation system's domain. Few researchers are working on identifying either the extreme opinions found on Web-blogs and other social media such as YouTube [95].

The identification of outlier opinions in the argumentation process is very useful. This information can help the decision maker in taking more appropriate actions during the decision making process. The information produced by the proposed framework helps the group to understand if they have reached an agreement in the context of decision issue. Opinions of the stakeholders are initially scattered in the opinion dimensionality. In a dialogue process, the decision making group might converge with the stakeholder with outlier opinion or they may even diverge. This result, however, helps a decision making group explore opinions as well. Using the information from the framework, the group might converge or diverge with the outlier opinions. In many situations during the argumentation process, stakeholders form polarization groups, and these groups influence others. In some instances a stakeholder's opinion might be further from any other individual in the decision making group in the opinion dimensionality.

Earlier argumentation systems never had this functionality. In a large argumentation process, when several stakeholders participate, contributing hundreds and thousands of arguments, both computing and analyzing the aggregate opinion of every stakeholder could be challenging. In this dissertation, a unique framework is presented to identify both stakeholders with outlier opinions and stakeholders with inliers opinions. This framework can address the above mentioned challenge.

A framework was previously developed to identify polarization groups in an argumentation system [4]. This framework is based on the similarity measurement. The framework in this chapter, however considers the dissimilarity of each stakeholder's opinion. Along with the dissimilarity between opinions, the mean opinion of the group is used to generate ranked list of stakeholders based on their dissimilarity values. We do not state that the outlier opinion is either a good opinion or a bad opinion to the decision making group within the context of a decision making issue. Our framework only identifies the outlier opinion. It is up to the decision making group on how to use the outlier opinions information.

The process of this framework is carried out in two folds (methods) for identifying outlier opinions. First, the outlier opinions are identified based on the aggregate opinion of a stakeholder. These opinions are computed by aggregating the strengths of the arguments posted by a stakeholder. In the second approach, the outlier opinions are identified based on the collective assessment scores received by a stakeholder through arguments. The collective assessment value of arguments are derived and aggregated. The aggregated collective assessment value of a stakeholder is used to identify the outliers. The results produced by these two methods are later analyzed and compared. A simple, distance-based outlier detection algorithm is implemented to identify both the outlier's and inlier's opinions in the intelligent argumentation system.

An individual's viewpoint is essentially, an individual's belief in an opinion vector. A collective viewpoint is an entire group's belief in an individual's opinion. Unique thoughts from the minority of participants in the decision making group needs to analyzed. Analyzing the outlier opinions can accelerate new discussions and possibly refine the stakeholder's opinions.

The following sections present the literature work, the proposed framework followed by experiments.

6.2. RELATED WORK

This section presents a brief state-of-the-art literature on opinion mining and analysis followed by a brief survey on outlier detection techniques.

6.2.1. Opinion Mining and Analysis. This section provides a brief overview on opinion mining and classification in social networks.

The textual information on Web can be broadly classified in two categories: facts and opinions [96]. Jindal and Liu [97] researched on opinion mining and analysis. Their primary objective was to detect and analyze the opinion spam written by reviewers on several products. They grouped reviews into three categories, namely Type 1(untruthful opinions), Type 2 (reviews on brands only), and Type 3 (non-reviews). Jindal and Liu have labeled some of the type 2 and type 3 reviews manually in order to carry out supervised learning. Labeling type 1 reviews was a challenging issue. Jindal and Liu performed analysis on the amazon data using Jaccard distance to identify the duplicate and near duplicate reviews. Spam reviews may exist in both duplicate and non-duplicate reviews. To identify type 2 and type 3 reviews, they build a model using logistic regression. They claim that the logistic regression worked well over support vector machine and naïve Bayesian classification. The logistic regression outputs the probability likelihood of a review being spam. Jindal and Liu [97] identified type 1 based reviews by dividing reviews into positive spam review and negative spam review. They are also classified on good quality, bad quality and average quality. Further, reviews are analyzed by identifying duplicate and non-duplicate reviews.

Bermingham et al. [95], researched sentiment analysis in social networking to explore potential for online radicalization. Bermingham et al. use the dictionary-based polarity scoring method to assign positivity and negativity scores to YouTube profiles and comments for the sentiment analysis. These scientists used automated crawlers which crawl across YouTube and collect data. User comments and user profile information were collected. These scientists developed a sentiment analysis engine earlier for analyzing blogs and they used the same system was used to analyze the YouTube data. The sentiment analysis engine [95] generates a score for each document based on the text parsing. It will compute the scores considering the positive and negative oriented terms in a document. There are two types of scores: positive sentiment score and negative sentiment score. Term frequency, document frequency and user frequency were used to computer the sentiment scores. The sentiment analysis scores are used in the social media.

Tang and Fong [98] in their article mentioned that the relations between users on social media sites often indicate correlation (negation) between user's opinions. Tang and Fong [98] studied the sentiment diffusion in large social networks. They researched the sentiment of people in social networks on several products, brands, politicians and so forth. Tang and Fong [98] claim that the polarity (sentiment) must be computed for a person rather than a document (comment). Capturing sentiment in a social group on Web is challenging since, it is hard to identify the hidden sentiment in the social context. Also the labels of the training data are not available which is difficult to do it manually [98]. In their model, unlabeled users and user's tweets are used from the network and the unlabeled data is predicted using multiclass SVM. In the model it is assumed that, influence is between the nodes only occurs within distance of 1.

Rabelo et al. [99], proposed a method for collective sentiment analysis which primarily considers social connections on social networks than processing text analytics. The researchers have evaluated their method by running it on political opinion analysis on twitter. A text based classifier was used to label the initial set of nodes for training purposes. A relational neighbor classifier combined with a relaxation labeling technique in order to perform the collective classification was used. Initially a text classifier will assign score by analyzing the text in a post. These scores represent labels which are then used for training purposes. In the second step, the collective classification algorithm receives the graph and the training labels for classification purposes.

Gokulkrishnan et al. [100], researched about sentiment and opinion analysis on twitter data. They used different classifiers to perform this task and evaluated their models based on the precision and recall. The objective behind their experimentation was to identify classifier that classifies tweets based on the expressed sentiment as neutral, polar and irrelevant. Polar is further classified into positive and negative. Gokulkrishnan [100] have conducted their experiments using several classifiers such as Naïve Bayes, Naïve Bayes multinomial, SVM, Random Forest and many more. They conclude that classifiers SVM and Random Forest performed well over other classifiers.

King et al. [101], present a survey of computational approaches used in social computing. Connectivity, collaboration and community [101] are the three characteristics that capture the essence of social computing.

Opinion analysis on movie reviews, product reviews, twitter data for political analysis and so forth are performed. Opinion analysis on blogs was also carried out but very less focus has been given to argumentation research for opinion and sentiment analysis. Research in social networks is carried out from community detection, polarization analysis, to viral marketing from social science perspective. Research on polarization analysis [1, 4] and argument analysis [6] has begun. But, research areas such as outlier opinion analysis in argumentation needs much more attention.

6.2.2. Outlier Detection Algorithms. Hawkins [94] stated that "Outliers are observations which deviate significantly from other observations as to arouse suspicion that these are generated by a different mechanism." Outlier detection techniques are crucial in data mining applications. Outlier detection algorithms have been utilized well in complex network systems.

In this dissertation, we intend to use the outlier detection techniques in the argumentation network. Several supervised outlier detection techniques and unsupervised outlier detection techniques are well explored and used across several domains.

Supervised outlier detection algorithms work by training data with the existing data labels provided. Unsupervised outlier detection techniques are more suitable in our application, as data labels are not available with the data. Most of the data that we work on is unlabeled. Gogoi et al. [102] broadly classified the outlier techniques into distance-based, density-based, and machine learning-based techniques. There are several other distance based statistical approaches and fuzzy logic based techniques to identify outliers. Several outlier detection algorithms such as K-nearest neighbor's method [103], local distance-based methods [104, 105], density-based outlier detection algorithms [106], evolutionary [107], Gaussian model, and LOF family of methods [108, 109, 110, 111] are well researched. Angle based outlier detection techniques [112] work by computing the dissimilarity among data points. This dissimilarity is computed using the angle between objects. These techniques work efficiently when the data consists of several dimensions. In social data based applications, this type of algorithms may be suitable. They are specially designed, however for data with large dimensions. The Euclidean distance metric can be used to compute the dissimilarity (i.e., distances between the objects).

6.3. FRAMEWORK

Figure 6.1 illustrates the proposed framework for both identifying and assessing outlier opinions in an argumentation process.

An argumentation tree is provided as input for not only processing but also analyzing the arguments. The framework will generate the ranked lists of stakeholders' opinions. Framework identifies outlier opinions based on stakeholder's individual viewpoint as well as from the collective viewpoint. Method 1 discusses how the outlier opinions are identified from the individual viewpoint. Method 2 discusses how the outlier opinions are identified from the collective viewpoint of individual's.

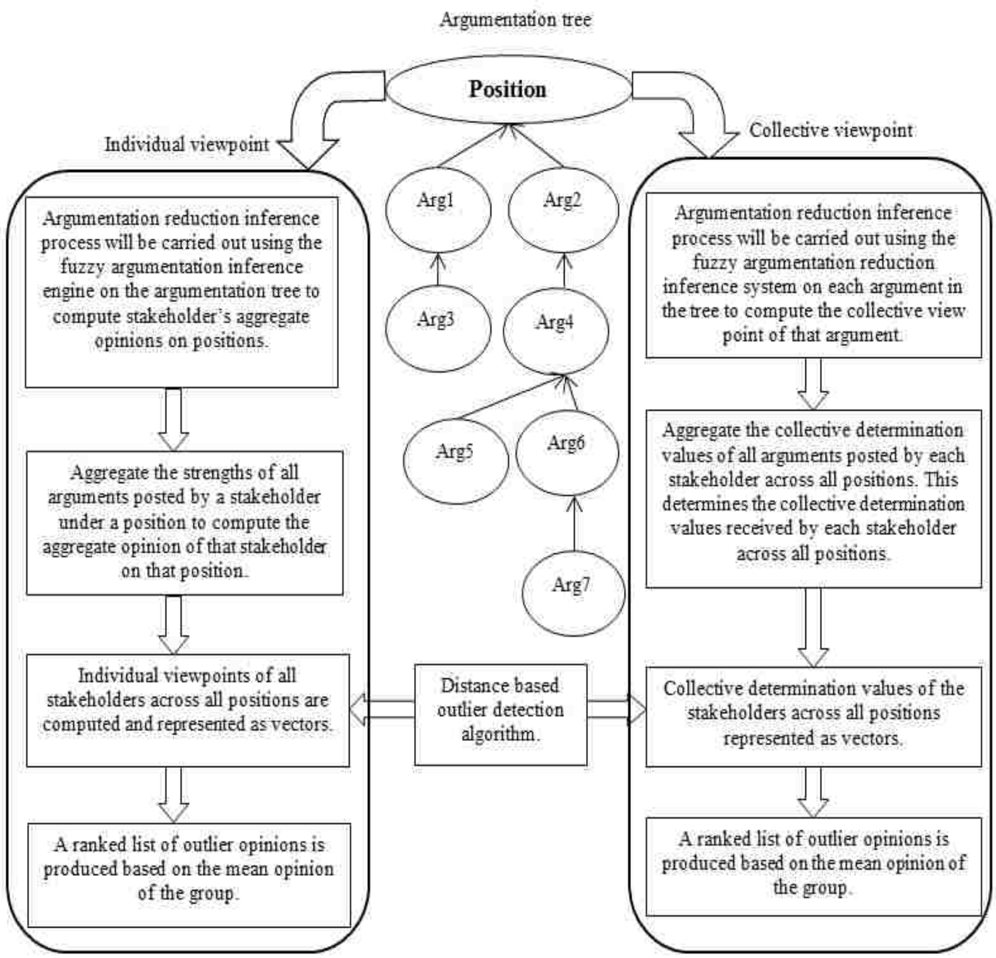


Figure 6.1. Framework for Identifying Outlier Opinions in the Argumentation System

6.3.1. Method 1 – Individual Viewpoint. In method 1, the system first computes the aggregate favorability of every stakeholder across each position in the argumentation tree. The argumentation inference system developed in our previous research [43, 49] is used to compute the aggregate favorability.

Step 1 - After the argumentation tree is constructed by the stakeholders, the framework is applied on the argumentation tree. In the first step of this framework, the system carries out the argumentation reduction inference process using the fuzzy argumentation reduction inference system on the argumentation tree. This process is conducted to compute a stakeholder's opinion.

The fuzzy argumentation reduction inference system is built upon the four fuzzy heuristic rules (section 2.2.3). In the argumentation tree, the arguments are either directly associated or indirectly associated with their respective positions. After the argumentation reduction process, arguments are directly associated with their respective positions. Initially, all arguments that are indirectly associated with the alternative in the argumentation tree are reduced to one level. This process is conducted until all arguments are directly associated with its alternative. This process is conducted with an argument reduction fuzzy inference system [43, 49].

The framework proposed in this chapter employs an argumentation reduction fuzzy inference engine to compute a stakeholder's favorability for an alternative. In Figure 6.2, stakeholder S2 has contributed three arguments under position 1. While one argument is directly associated with position 1, the other two are associated with the arguments posted by stakeholder S1.

The fuzzy inference rules are used for the argumentation reduction process. The association between (Arg1, position 1) and (Arg4, Arg1) are considered for using the appropriate fuzzy inference rules, see Figure 6.2 and Figure 6.3. Based on the suitable fuzzy inference rule, Arg4 is reduced level by level such that it is directly associated to Position 1. The same procedure was conducted for Arg6. The system ensures that all arguments posted by a stakeholder are directly associated with an argument. The argument-based fuzzy inference system then reassesses the strengths of the arguments based on the inference rules. The new strength that an argument is assigned is relative to the solution alternative.

See Figure 6.3 for the argumentation tree after the fuzzy inference process. The favorability of stakeholder S2 for position 1 is the aggregate of the argument's strength: Arg4, Arg2, and Arg6 (see Figure 6.3). Similarly, the favorability of stakeholder S2 for positions 2 and 3 are derived.

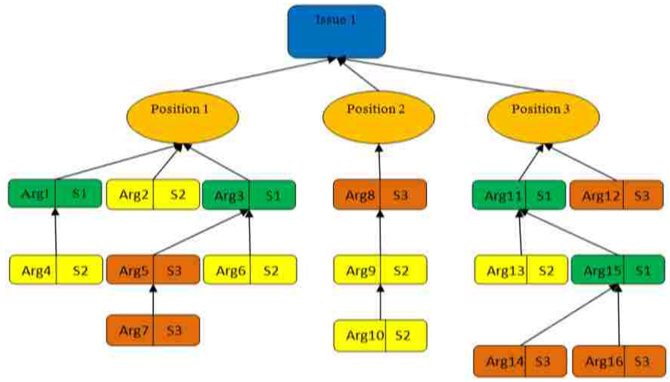


Figure 6.2. Argumentation Tree before Argumentation Inference

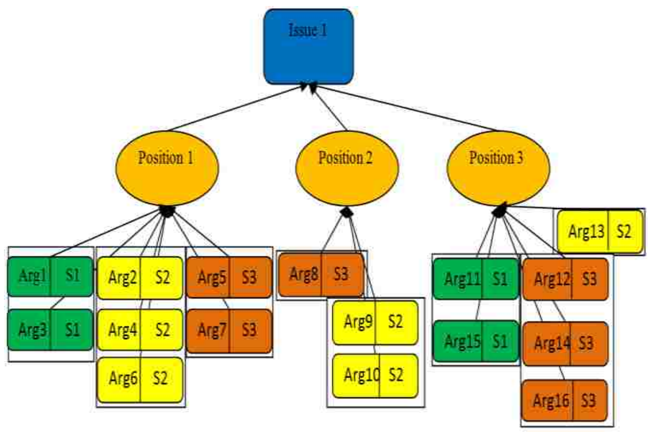


Figure 6.3. Argumentation Tree after Argumentation Inference

Step 2 - After the argumentation reduction inference process, the strength of the arguments posted by a stakeholder is aggregated to compute the overall favorability of a stakeholder for that alternative. The system then computes the stakeholder's favorability for each position to compute a stakeholder's favorability for that position. The argument's strengths posted by a stakeholder under a position are aggregated after the inference process. This aggregation is conducted to compute the aggregate trust of a stakeholder for that position. The trust of all stakeholders is computed with respect to each position posted in the argumentation tree.

The favorability of a stakeholder for all of the alternatives is represented as a vector. This vector is known as an opinion vector. Each element in the opinion vector presents the favorability of a stakeholder for a position.

Step 3 - The favorability of a stakeholder for all of the positions is represented as a vector, also known as an opinion vector. Each element in the vector represents a stakeholder's trust in the position. The opinion vectors can be represented in the opinion dimensionality. The opinion vectors are normalized using the min-max normalization technique (Eq. 1). For example, stakeholder S2's opinion can be represented as (x1, x2, x3), where x1, x2, and x3 represent S2's favorability for position 1, position 2, and position 3 respectively.

$$v' = \frac{v - \min A}{\max A - \min A}(new\_\max A - new\_\min A) + new\_\min A \qquad (9)$$

Where min A and max A represent the minimum and the maximum values in the data set, respectively. We assign new_max A to +1 and new_min A to -1, as we want the new data to be normalized within the range of -1 and +1.

Step 4 - The distance-based outlier detection algorithm (Algorithm 3) will be applied on the vectors to generate a ranked list. The ranked list is generated based on the opinion vector's distance with the mean opinion of the group. A simple distance based outlier detection algorithm was implemented on the opinion vectors. Several distance-based techniques can also be used here. The algorithm initially computes the mean vector using the input vectors provided. The algorithm next computes the distance from each opinion vector to the mean opinion. The distance value presents the dissimilarity between each input opinion vector and the mean opinion vector. After the distance values are obtained, the opinion vectors are arranged in a descending order to present the ranked list.

Algorithm 3 - Distance Based Dissimilarity Algorithm

Input: Opinion vectors
Output: Ranked list of opinions based on the farthest from the mean opinion of the group.

Step1 – Compute the mean vector (X) of the input opinion vectors (Y).
Step2 – Compute the Euclidean distance (Eq. 10) from the mean opinion vector and all input opinion vectors.
Step3 – Sort and generate the ranked list based on the distance between opinion vector and mean vector.

$$D(X,Y) = \sqrt{(X1 - Y1)^2 + (X2 - Y2)^2 + (X3 - Y3)^2} \qquad (10)$$

Step 5 - This step discusses the ranked list generated in the last step. The ranked list generated in the previous phase is used to analyze the results. The top stakeholder (opinion) in the list represents the opinion furthest from the mean opinion of the group. The last element in the generated list represents the opinion closest to the mean opinion of the group. This list helps both decision makers and stakeholders better understand the argumentation process within the context of outlier opinions. The top – K list of outlier opinions can also be generated using the list produced in the last step. The top – K values in the list would be the top – K outlier opinions; the rest would be the inliers opinions.

6.3.2. Method 2 – Collective Viewpoint. In order to detect outlier opinions of participants from a collective perspective, we will first compute the collective trust received by a stakeholder's arguments under a position and aggregate all collective trust values received by that stakeholder under each position.

Step 1 - After the argumentation process, the argumentation reduction inference process is conducted using the fuzzy argumentation reduction inference system. Each argument's collective determination value will be derived using the inference system (Figure 6.4). In method 1, the argumentation reduction process was conducted on a tree alternative. Here, however, the argumentation reduction process is conducted on each and every argument to compute the favorability of each argument from other arguments in the tree. The four fuzzy heuristic rules (section 2.2.3) are used in the fuzzy inference system.

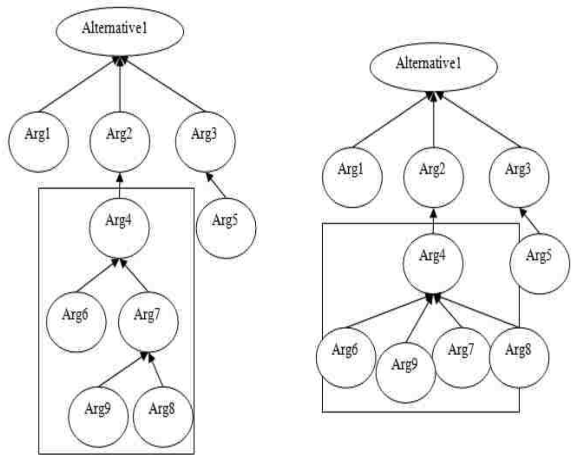


Figure 6.4. Computing Collective Determination of Arguments

Step 2 - In this step, the collective determination values of all arguments are aggregated for each stakeholder under a position. The aggregate collective determination of a stakeholder on all positions is derived. Collective determination scores of each stakeholder are represented as a vector. This process will be conducted for all the arguments and stakeholders in the argumentation process.

Each element in a vector represents the aggregate collective determination that a stakeholder's arguments have received under a position. The vectors are then normalized using the min-max normalization technique (Eq. 9) to attain consistency in the data. A detailed explanation is provided on how the collective trust value of an argument is derived using the argumentation inference engine in earlier section.

The total collective determination received by a stakeholder under a position represents the support received by that stakeholder under that position. This process is conducted for all stakeholders across all positions posted under an issue in the argumentation tree. The distance-based outlier detection algorithm (Algorithm 1) is used here to produce the ranked list of outlier opinions from the collective viewpoint.

Step 3 - Collective determination values of stakeholders, across all positions, are represented as vectors. A collective determination vector of a stakeholder has three elements if there are three different positions in a tree. Each element represents the aggregate collective determination value that a stakeholder's arguments have received under a position. For example, stakeholder S3's collective determination vector can be represented as (c1, c2, c3), where c1, c2, and c3 represent the aggregate collective determination that S3's arguments received from other arguments under position 1, position 2, and position 3, respectively.

Step 4 - The distance-based outlier detection algorithm presented in algorithm 3 is employed here to identify both the inlier and the outlier opinions.

Step 5 - The ranked list generated in the last step is used to analyze the results. The top stakeholder (opinion) in the list represents the opinion furthest from the mean opinion of the group. The last element in the generated list represents the opinion closest to the mean opinion of the group. The list generated here is from the group's perspective.

In some cases, a few stakeholders may not have presented their opinion in the argumentation system. If a stakeholder has not participated in the argumentation process, the system cannot process this stakeholder's opinion. This is not the framework's problem. However, the system currently assigns the opinion value as zero when a stakeholder has not presented his opinion.

6.4. EVALUATION

This section presents two different small scale studies carried out at Missouri University of Science and Technology. The first study was conducted in 2010 and the second study was conducted in the year 2013. Results in the second study are validated by the participants.

6.4.1. Empirical Study 1. An experiment was conducted in early 2010 [8] by recruiting twenty-four students from the software engineering class. Students were provided with the case study, a decision issue, and positions pertaining to the case study. Students participated in the argumentation process using the intelligent argumentation system. The data in these experiments is from real discussions.

6.4.1.1 Objective. The objective of this experiment is to evaluate the proposed framework and identify the outlier and inliers opinions based on the two methods presented and evaluate the results produced.

6.4.1.2 Case study. This experiment was based on a hypothetical case study. The subject of the case study was the adoption of software metrics during a software development life-cycle. A large, private organization was working on a special project which is important. The adoption of software metrics program is important. Selecting the appropriate metrics package was a decision challenge provided to the decision making group. After the argumentation system was provided to the stakeholders, stakeholders spent more than one week exchanging arguments. A tree with 204 arguments was built by the stakeholders.

Issue - Selection of software metrics program for a large scale organization for the given project described in the given case study.

Positions

Comprehensive metrics program

Light metrics program

No metrics program

Sample arguments - The following two arguments are sample arguments posted by stakeholders in the tree. These arguments were randomly chosen. Each is directly attacking the no metrics program.

Argument 1 - A large organization will have huge projects and huge number of employees. If there is no metric program in place it might be very difficult to

1. Manage the effort and productivity of the employees.

2. Determine and improve quality of the product.

3. Make proper estimation for the future projects

Argument 2 - To improve the quality of software products it is crucial to enhance the quality of the software process used to develop it. The primary target for any organization in the competitive world is to improve it sales which signifies that the organization should produce quality products. To improve the quality of software products it is important to enhance the quality of the software processes used to develop software. In a large scale organization to enhance the quality of software process each tasks needs to be performed with at most care by assigning the tasks to respective people. So it has huge number of employees. In order to have good communication and co-operation between all the employees we need good software metrics.

6.4.1.3 Experiment procedure. Initially, the twenty-four stakeholders in the decision making group were provided with both the decision-making issue and the relevant positions posted in the argumentation tree. Stakeholders exchanged arguments over different positions for one week. After the argumentation tree was constructed, the developed framework was applied on the argumentation tree. Both the individual perspective and the collective perspective sub-frameworks were applied on the tree. This framework then produced the results explained in detail in the following sub-sections.

6.4.1.4 Results. The following results were produced using method 1 (individual method) in the framework of an argumentation tree constructed by twenty-four stakeholders. Figure 6.5 is a three-dimensional plot, where position 1, position 2, and position 3 represent the x-axis, y-axis, and z-axis, respectively. Each data point represents an opinion across the three axes.

Figure 6.6 represents a three-dimensional figure plotted after the framework was applied on the argumentation tree. The data points in blue are the outlier opinions in Figure 6.6. The top-5 outliers from the ranked list are included as well.

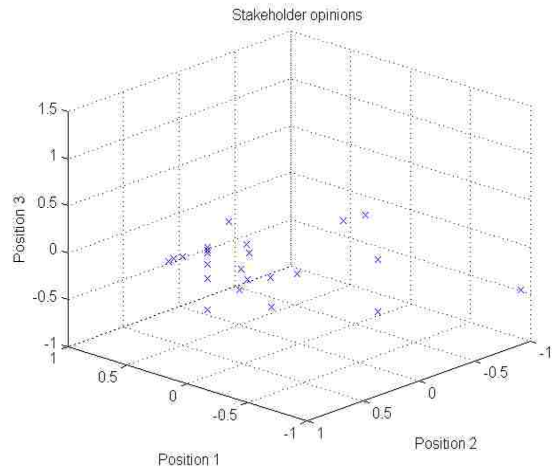


Figure 6.5. Individual Opinion Vectors Plotted on 3-D Plot

Table 6.1 presents the ranked list of stakeholder opinions. Table 6.1 presents outliers and inliers opinions based on the individual method. S18 is the opinion of stakeholder number eighteen. Stakeholder S18 ranks one in the outlier ranked list, while stakeholder S7 is ranked one in the inlier's ranked list. Stakeholder S18's opinion is furthest from the mean opinion of the group, while stakeholder S7's opinion is closest to the mean opinion of the group.

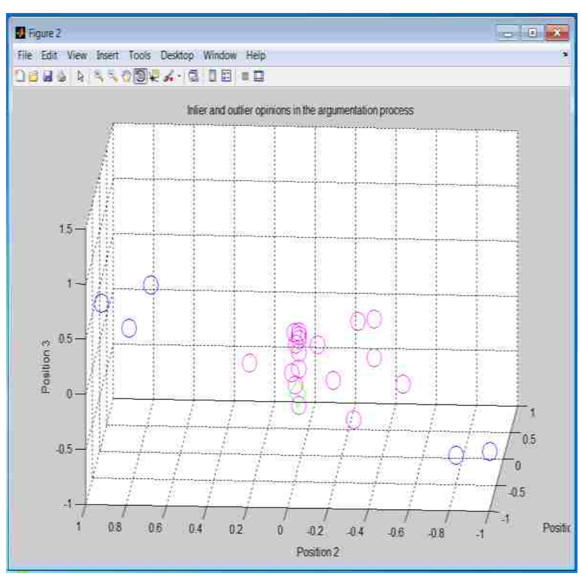


Figure 6.6. Outlier Opinions Identified By the Framework Based On the Individual Method

Table 6.1. Ranked List of Stakeholders with Outlier and Inlier Opinions Based on the Individual Method

Ranked list of outliers based on the farthest opinion from the mean opinion of the decision making group	Ranked list of inliers based on the closest opinion from the mean opinion of the decision making group
S18, S19, S21, S23, S9, S17, S12, S20, S16, S2, S8, S5, S4, S14, S15, S1, S10, S11, S22, S3, S24, S6, S13, S7	S7, S13, S6, S24, S3, S22, S11, S10, S1, S15, S14, S4, S5, S8, S2, S16, S20, S12, S17, S9, S23, S21, S19, S18

A decision maker can also generate the top-K list of stakeholders, with both outlier and inlier opinions, using the results in Table 6.1. Table 6.2 presents the results by the framework when K = 5. The results in Tables 6.1 and 6.2 were generated according to stakeholder's opinions.

Table 6.2. Top-K Stakeholders with Outlier Opinions Based on the Individual Method

Stakeholders with outliers opinions	Stakeholders with inliers opinions
S18, S19, S21, S23, S9	S17, S12, S20, S16, S2, S8, S5, S4, S14, S15, S1, S10, S11, S22, S3, S24, S6, S13, S7

The results in Tables 6.3 and 6.4 were produced with the collective outlier method in the framework on the argumentation tree. This method identified outliers based on the collective determination factor of each stakeholder across all positions. Tables 6.3 and 6.4 present the outlier opinions in a decision making group from the group's perspective.

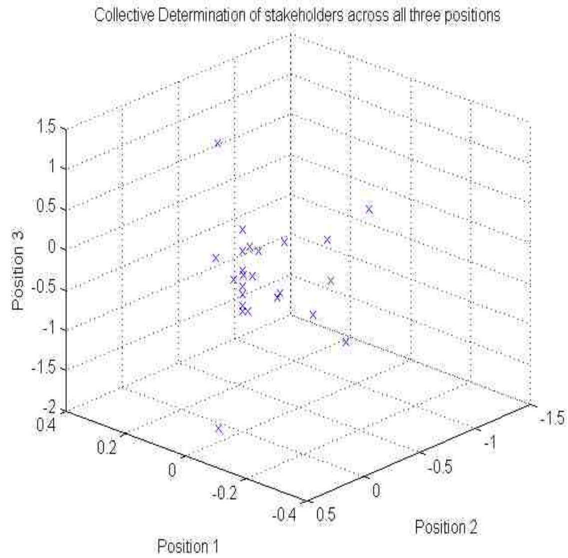


Figure 6.7. Collective Opinion Vectors Plotted On 3-D Plot

Figure 6.7 presents the stakeholders' vectors. These vectors were computed from the collective determination received on stakeholder's opinion by the group. Figure 6.8 presents a three-dimensional figure of the top-5 outlier opinions identified by the collective outlier identification method. The blue data points are the outlier opinions; the rest are the inlier opinions.

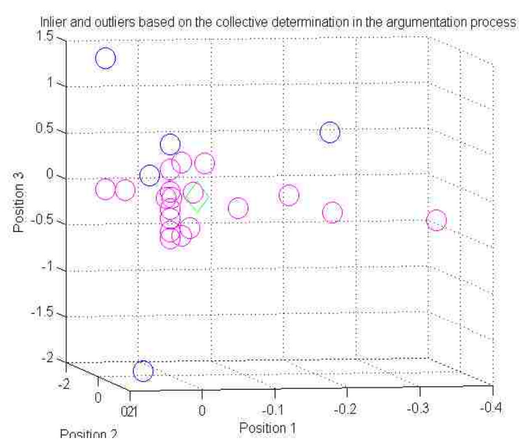


Figure 6.8. Outlier Opinions Identified By the Framework Based On the Collective Method

Table 6.3 presents the ranked list of both stakeholders with outlier opinions and stakeholders with inlier opinions. Stakeholder S20's opinion is an outlier with respect to the group's opinion and is ranked one. S2's opinion is ranked one in the inlier's list. The results in Table 6.3 are from the collective perspective of the group. Table 6.4 presents the top-5 list of outliers. The remaining are identified by the group as inlier opinions. Figure 6.8 was plotted according to the results from Table 6.4.

Table 6.3.Ranked List of Stakeholders with Outlier and Inliers Opinions Based on the Collective Method

Ranked list of outliers based on the farthest opinion from the mean opinion of the decision making group	Ranked list of inliers based on the closest opinion from the mean opinion of the decision making group
S20, S8, S23, S17, S22, S19, S12, S21, S13, S24, S5, S10, S9, S3, S4, S16, S11, S6, S14, S1, S18, S7, S15, S2	S2, S15, S7, S18, S1, S14, S6, S11, S16, S4, S3, S9, S10, S5, S24, S13, S21, S12, S19, S22, S17, S23, S8, S20

Table 6.4. Top-K Stakeholders with Outlier Opinions Based on the Collective Method

Outliers	Inliers
S20, S8, S23, S17, S22	S19, S12, S21, S13, S24, S5, S10, S9, S3, S4, S16, S11, S6, S14, S1, S18, S7, S15, S2

6.4.1.5 Analysis and discussions. Table 6.5 presents further analysis of the results produced by both methods.

Table 6.5. Ranked List of Outliers Based on both Individual and Collective Methods

Ranked list of outliers based on the farthest opinion from the mean opinion of the decision making group based on the stakeholders' individual opinions.	Ranked list of outliers based on the farthest opinion from the mean opinion of the decision making group based on stakeholders' collective determination values.
S18	S20
S19	S8
S21	S23
S23	S17
S9	S22
S17	S19
S12	S12
S20	S21
S16	S13
S2	S24
S8	S5
S5	S10
S4	S9
S14	S3
S15	S4
S1	S16
S10	S11
S11	S6
S22	S14
S3	S1
S24	S18
S6	S7
S13	S15
S7	S2

We could use this information to determine both the ranking and the overlap of rankings in the outlier opinion ranks (e.g., see rank 7 in Table 6.5). Stakeholder S12's opinion is ranked as outlier number seven from both the individual method as well as the collective determination method.

The following four different cases can be analyzed:

- From an individual's perspective, his opinion is an outlier. From the collective perspective, his opinion is not an outlier.
- From an individual's perspective, his opinion is not an outlier. From a group's perspective, his opinion is not an outlier.
- From an individual's perspective, his opinion is an outlier. From the group's perspective, his opinion is an outlier.
- From an individual's perspective, his opinion is not an outlier. From the group's perspective, his opinion is an outlier.

The results presented in Table 6.5 will fall into one of the cases explained above. This classification provides a better understanding of the opinions in a decision making group. It also allows to better understand the dynamics involved in a decision making group during an argumentation process.

The results produced by the proposed framework helps both a decision maker and the decision making group not only analyzes the results but also make more informed decisions. These results can also help decision makers understand the overall group opinion, inliers, and outlier opinions. The decision maker can also discuss outlier opinions with various stakeholders.

We do not claim that a stakeholder with an outlier opinion is either good or bad. Our model simply identifies the outlier opinions and allows the group to decide on how best to use this information.

6.4.2. Empirical Study 2

6.4.2.1 Background. In this experiment fourteen students from the e-commerce business class were recruited to participate in our study. The fourteen students played the role of stakeholders and participated by posting arguments in the argumentation tree. The team of fourteen stakeholders were provided with the background case study and the decision making issue to be resolved. After participating for around ten days, an argumentation tree was constructed which consisted of thirty five arguments.

6.4.2.2 Case study. The issue was about the death of Aaron Swartz [56, 57]. Aaron Swartz was an American computer programmer, writer, political organizer and internet activist. He founded the online group demand progress, known for its campaign against the stop online piracy act. Aaron was charged for downloading thousands and millions of articles illegally from JSTOR archive using MIT's open network. If proven to be guilty Aaron would face up to thirty five years of prison and a fine up to $1 million. On January 11th, 2013 two years of after his arrest, Aaron had hanged himself in his apartment.

Issue – What happened with Aaron Swartz? Who is at fault for Aaron Swartz killing himself?

Position 1 – The laws, attorneys and MIT who pushed the case?

Position 2 – Not anybody's fault. It's not the Government's or MIT's fault in anyway. The rules have to be followed in any means.

6.4.2.3 Objective and framework. The objective of this experiment was to evaluate the outlier detection assessment framework with a real world issue. The participating stakeholders were provided with a detailed background about the case and how to use the system. Each stakeholder was provided with a unique username and password to log-on to our intelligent argumentation system to participate in the discussion. Around ten days of time was given to the stakeholders to participate in the dialog process. After the discussion process, the outlier detection assessment framework was run on the discussion tree to identify the outlier opinions. The results generated by the framework were given to the stakeholders to validate.

6.4.2.4 Process and observations. The fourteen stakeholders participated in the discussion process using the intelligent argumentation system which was followed by the application of outlier detection framework on the discussion. The top K value was provided as three when the framework was used on the argumentation tree. The framework identified three outlier opinions and the participants associated with those opinions. Figure 6.9 presents the opinion vectors of participants computed by the framework which are plotted in the opinion dimensionality. The results generated by the framework were given to the stakeholders to validate. Please see Figure 6.10 for the validation results. After the framework generated the outlier opinion results, they were presented to the stakeholders as a survey. Eight participants agreed with the result produced by the system. Four participants were neutral in their opinion and two participants disagreed with the result.

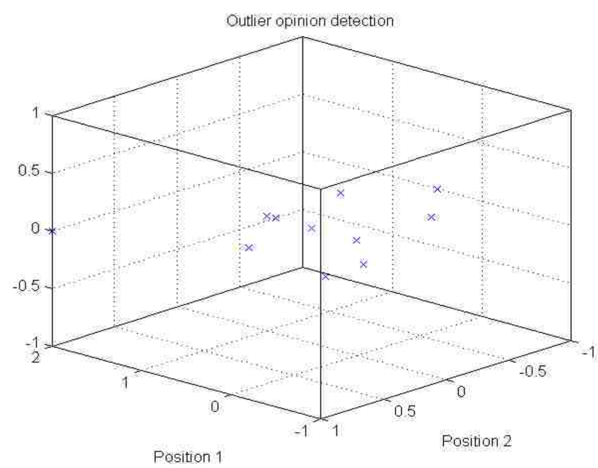


Figure 6.9. Opinion Vectors of Participants Plotted in the Opinion Dimensionality

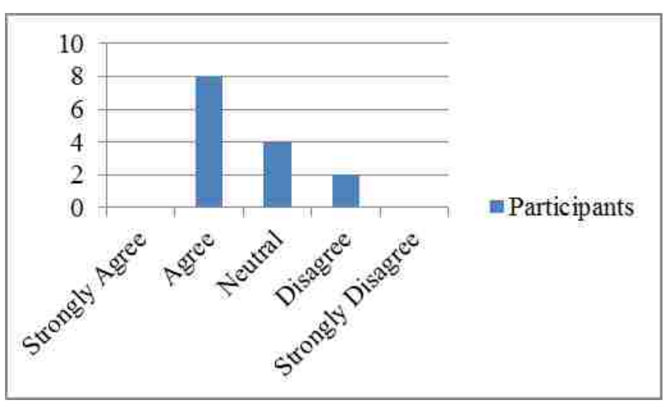


Figure 6.10. Outlier Opinion Detection Framework Results Validation by Participants

6.5. FINAL REMARKS

The results produced by the proposed framework helps both a decision maker and the decision making group not only analyzes the results but also makes more informed decisions. These results can also help decision makers understand the overall group opinion, inliers, and outliers opinions. The decision maker can also discuss outlier opinions with various stakeholders. We do not claim that a stakeholder with an outlier opinion is either good or bad. Our model simply identifies the outlier opinions and allows the group to decide on how to use this information.

7. CASE STUDY AND EMPIRICAL STUDY OF INTELLIGENT ARGUMENTATION SYSTEM

Section 7.1 in this chapter presents the air traffic management case study. Section 7.2 presents the empirical evaluation which is conducted to compare the argumentation system and the email system for collaborative decision support.

7.1. AIR TRAFFIC MANAGEMENT STUDY

7.1.1. Introduction. In this section, we present an approach on how the intelligent argumentation based collaborative decision support system can facilitate resolution of conflicts in air traffic management. It could enhance the Ground Delay Program (GDP) and help the Air Traffic Control System Command Center (ATCSCC) to take a better decision depending on the argumentation of Air Route Traffic Control Centers (ARTCC) and stakeholders from different airlines.

Collaborative Decision Making (CDM) is one of the most important aspects in any industry. One such industry is air traffic management. Every decision in this industry made is in a high-level, strategic scenario. The National Airspace System (NAS) in the United States is the most complex aviation system in the world. It is divided into 21 zones known as Air Route Traffic Control Centers (ARTCC). In this application environment, the stakeholders are geographically distributed across the country, and the decisions made are mission critical.

In this section, we explain how the intelligent argumentation system can be used in enhancing the Ground Delay Program (GDP) by demonstrating the technique through a developed and tested hypothetical case study. The case study was carried out in a controlled environment in our laboratory. The decision making process in a GDP program involves stakeholders such as Air Traffic Control System Command Center, Air Route Traffic Control Center, Airlines and other NAS users.

7.1.2. Background. One of the primary objectives of Federal Aviation Administration (FAA) is to both plan and apply strategic initiatives to advocate anticipated demand-capacity imbalances at airports [113]. If an imbalance is expected at an airport, traffic managers apply ground delays to flights bound for the troubled airport commensurate with the delays they would receive in an airborne queue [114]. The FAA is responsible for handling ground delay program situations. Ground delay programs typically occur due to bad weather conditions. These bad weather conditions limit the number of flight operations possible. As flight operations are reduced, several airlines incur heavy financial losses. The current GDP rations the available arrival slots at the affected airport by scheduled arrival time of the flights with some adjustments. These adjustments are made to balance the equity between airlines. Current rationing rules do not take into account passenger flow efficiency in rationing assignment tradeoffs [118]. Both Air Traffic Control (ATC) specialists and CDM participating airlines use Flight Scheduled Monitor (FSM), developed by Metron Aviation Inc., to both monitor and model traffic flow management. Many scientists have examined different GDP rationing rules to achieve fairness among airlines. Fairness is interpreted as allocating delays equally among airlines. Several methods were used to determine how to distribute delays among airlines.

The FAA command center also known as ATCSCC, other FAA facilities, and the airlines use a software program, Flight Schedule Monitor. The Flight Schedule Monitor software displays Airport Demand List (ADL) information, monitor the airport-traffic situation, and collaborate on other problems. Flight Schedule Monitor both imports and displays ADL data. This list enables all FAA and airlines to view airport demand and capacity, to list flights, to produce flight counts and statistics, and to color-code flights according to a variety of fields. Flight Schedule Monitor provides two displays: a very detailed timeline display and an aggregate bar graph. A situation that could require a ground delay program is indicated when the airport capacity line on the bar graph drops below a certain threshold [113].

None of these developed models consider the problems associated with the airlines. Instead they pay strict attention to both the fairness and efficiency of the model. Airlines have a very limited opportunity to both discuss and argue with the FAA command center for the slot allocations in the present system. This is the major drawback of the existing systems. Air traffic flow management can be improved by generating better information. This can be achieved by combining information generated by both FAA and NAS users, and distributing the same information both to FAA and NAS users [115]. The case study here examines how ATCSCC, ARTCC, and airlines participate in the discussion process for slot allocations using the intelligent argumentation system.

7.1.3. Significance. The airline industry remains a large and growing industry. The central idea of the air transportation system is to be cost-effective, rapid, and safe transportation of both passengers and cargo. It facilitates economic growth, world trade, and international investments. The air transportation system is a significant engine of the national economy, providing a service that cannot be achieved by other modes of transportation [116]. During peak hours in air travel in the United States (US), approximately 5,000 flights per hour fill the sky. This number is equivalent to approximately 50,000 flights operating in National Air Space (NAS) every day.

Ground Delay Program (GDP) was implemented to control air traffic volume around airports. GDP is implemented when the projected traffic demand is expected to exceed the airport's acceptance rate for a lengthy period of time. Demand exceeding the acceptance rate is normally a result of the airport's acceptance rate being reduced. Weather is the most common reason for a reduction in the acceptance rate. Low ceilings, low visibility, snow, and thunderstorms are some of these.

Between 1999 and 2006, averages of 960 GDP programs per year were declared around the United States. During the first five months of 2007, more than 25 percent of domestic flights arrived more than 15 minutes late [117]. During the Ground Delay Program, the number of flights that should be operated must be reduced to a given level. The imbalance between demand for flights and available capacity is estimated to cost passengers between $3 billion and $5 billion a year in trip delays [118].

During the GDP program, the Air Traffic Control System Command Center (ATCSCC) needs to downsize the number of flight operations for each airline to achieve a balance between the demand for flights and the airport acceptance rate. Thus, the

ATCSCC must make a reasonable solution to reduce the flight operations in each airline while maintaining fairness among all airlines. The ATCSCC needs to ration the flights among all airlines. Sometimes the airlines may not be happy with the number of flight operations allocated to them.

The web-based intelligent computational argumentation-based conflict resolution system allows the airlines to argue the issues for which they are unsatisfied. The following section focuses on a hypothetical case study, developed and tested on the intelligent argumentation system. This system introduces argumentation among the ATCSCC, the ARTCC, airlines and other National Air Space users. By using intelligent argumentation system, the ATCSCC can better understand problems of airlines and other stakeholders through their arguments and take a better decision. There will be an improvement in the quality of information exchange and it could possibly enhance the GDP planning process. Ultimately, our system can improve collaborative decision making among stakeholders.

7.1.4. Case Study. Let us suppose that, due to incremental weather conditions, a large-hub airport, such as Chicago ORD, decides to reduce its operational capacity. This reduction will initiate the GDP program. Reducing the flight operations will need to be discussed via a conference-call among stakeholders at ATCSCC. In our case study, the ATCSCC will post both the issue and its possible positions in the intelligent argumentation system. Other stakeholders can also post their positions if they believe the positions meet the criteria set by the ATCSCC.

7.1.4.1 The issue. Let us assume that the Chicago ORD airport has 100 flight operations per hour. Due to the GDP program, these flight operations must be reduced to 45 – 60 operations per hour. The length of the GDP affected period is assumed to be one hour. The GDP program is also assumed occur during the day. Airlines1 has its hub in the Chicago ORD airport. Airlines 3 operate more international flights than domestic flights during the GDP affected hour. Table 7.1 illustrates all of the airlines involved in this case study.

Table 7.1 illustrates that Airlines 1 is operating 40 flights per hour. Airlines 2 has 24 operations per hour, and Airlines 3 has 36 flight operations per hour. Airlines 3 operate with more passengers over the other two airlines. It also has more international than domestic flights during that GDP affected hour.

Table 7.1. Flight Operations of Airlines

Airlines	Flight operations / hour
Airlines 1	40 operations / hour
Airlines 2	24 operations / hour
Airlines 3	36 operations / hour

7.1.4.2 The stakeholders. Stakeholders are individuals who either can affect or are affected by the achievement of an objective in a project. We had five stakeholders involved in our decision making process. ATCSCC was utilized as the command center. Their role was to manage the flow of air traffic within the continental United States. ARTCC was responsible for controlling the instrument flight rules for aircraft en route, in a particular volume of airspace, at high altitudes. We used three airlines: Airlines 1, Airlines 2, and Airlines 3. Each stakeholder was given a priority in the system. Priority value ranges between 0 and 1. A higher value priority implied a higher influence in the decision making scenario. A lower value priority implied a lower influence. This priority was used to assess the strength of an argument. This influences the favorability factor of an alternative. Table 7.2 presents the priority of each stakeholder in this case study.

Table 7.2. Priorities of the Stakeholders

Stakeholder	ATCSCC	ARTCC	Airlines 1	Airlines 2	Airlines 3
Priority	0.9	0.6	0.3	0.3	0.3

7.1.4.3 The positions. An alternative, or a position, is a choice limited to one of two or more possibilities for the given decision problem. ATCSCC posts the decision issues along with the positions. The following hierarchy (Figure 7.1) illustrates all of the positions for the given issue.

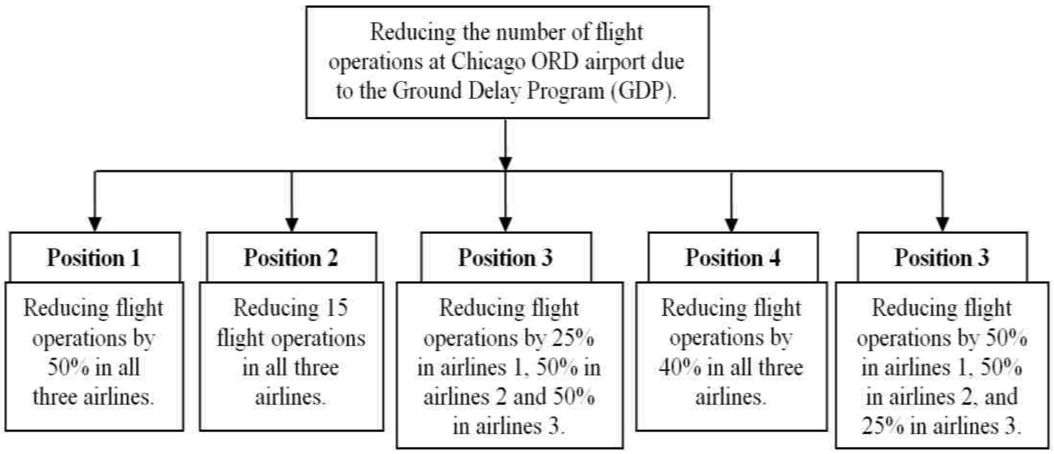


Figure 7.1. Five Positions for the Given Decision Making Issue

Five alternatives were posted for the given decision making issue. The first two positions are provided by the ATCSCC, and the remaining three positions are provided by the airlines. Each position was a plan. Each position actually tells how the flight operations slots have to be assigned to each airline. The first two alternatives followed the equity, and all of the airlines were given an equal number of operational slots. Fairness existed among the airlines in the first two alternatives. The third alternative was posted by airlines 1, the fourth by airlines 2, and the fifth by airlines 3. All of the three positions posted by the airliners were in their own favor. Each position obeyed the criteria set by the ATCSCC for an alternative. The total number of flight operations had to be between 45 and 60. The following description provides a detailed discussion about the five positions.

Position 1 – Reducing flight operations by 50% in all three airlines. This reduction indicates that airlines 1, 2, and 3 had to reduce their flight operations by 50%.

Position 2 – Reducing fifteen flight operations in all three airlines. This reduction indicates that airlines 1, 2, and 3 had to reduce 15 flight operations from each of their schedules.

Position 3 – Reducing flight operations by 25% in Airlines 1, 50% in Airlines 2, and 50% in Airlines 3. This reduction indicates that Airlines 1 could operate 75% of their scheduled flights. Airlines 2 can operate only 50% and Airlines 3 can operate only 50% of their scheduled flights. This position was originally posted by Airlines 1. This alternative was intuitively favorable to airlines 1.

Position 4 – Reducing flight operations by 40% in all three airlines. This position indicates that all three airlines can only operate 60% of their total scheduled flights. This position was posted by airlines 2 in their favor.

Position 5 – Reducing flight operations by 50% in Airlines 1, 50% in Airlines 2, and 25% in Airlines 3. This position was posted by airlines 3 in their own favor. This position allowed airlines 3 to operate 75% of their scheduled flight by cutting down only 25% of their flight operations, while Airlines 1 and Airlines 2 can only operate 50% of their scheduled flight operations.

Table 7.3 shows the total number of flights allocated to each airline according to each alternative.

Table 7.3. Five Positions for the Issue and Their Flight Slot Allocation

	Reducing flight operations by 50% in all airlines.	Reducing 15 flight operations in each airline.	Reducing 25% in Airlines 1, 50% in Airlines 2, 50% in Airline 3.	Reducing flight operations by 40% in all airlines.	Reducing 50% in airlines1, 50% in airlines2, 25% in airlines3.
Airlines 1	20	25	30	24	20
Airlines 2	12	9	12	14	12
Airlines 3	18	21	18	21	27
Total flight operations	50	55	60	59	59

7.1.4.4 The argumentation framework. This section explains how the web-based intelligent argumentation system is used in air traffic management. Initially, the ATCSCC center identifies both the issues and its possible positions. The stakeholders then participate in the argumentation process by posting arguments on the positions listed by ATCSCC. They can post their arguments either against an alternative or in support of it. They can also post supporting evidences. Additionally, an argument can either support or attack another argument. Once the argumentation process is complete, the system computes the favorable position. The output of the system is the favorability value of all five positions posted in the tree. Figure 7.2 illustrates the argumentation framework of the application of air traffic management in a web-based intelligent computational argumentation system.

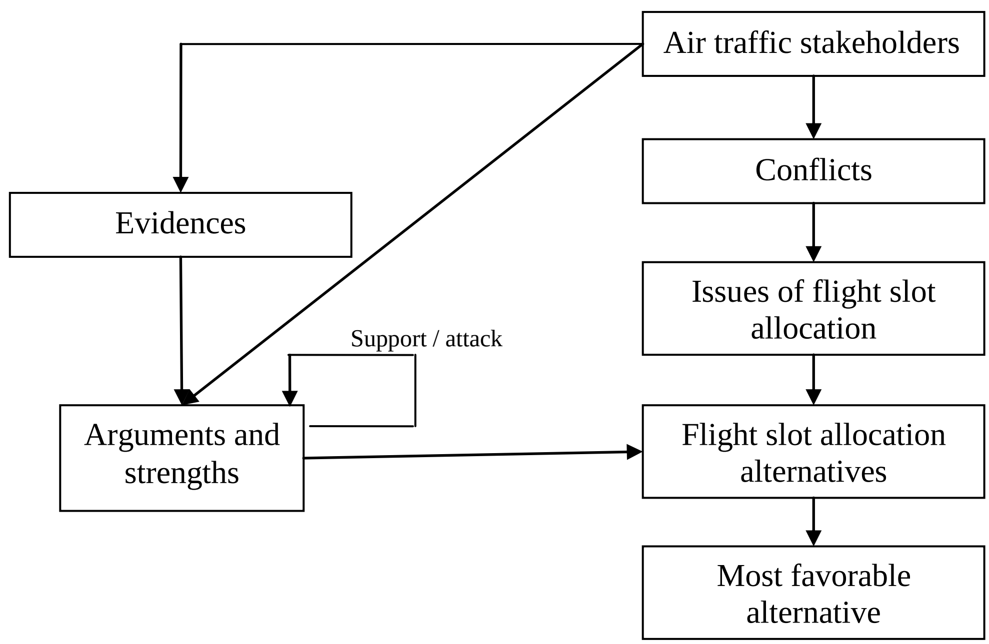


Figure 7.2. Argumentation Framework for Conflict Resolution in Air Traffic Management

7.1.4.5 The argumentation tree. The web-based intelligent computational argumentation tool is a logic-based framework for argumentation process. Figure 7.3

presents a snapshot of the argumentation tree of the flight slots allocation decision issue in the air traffic management.

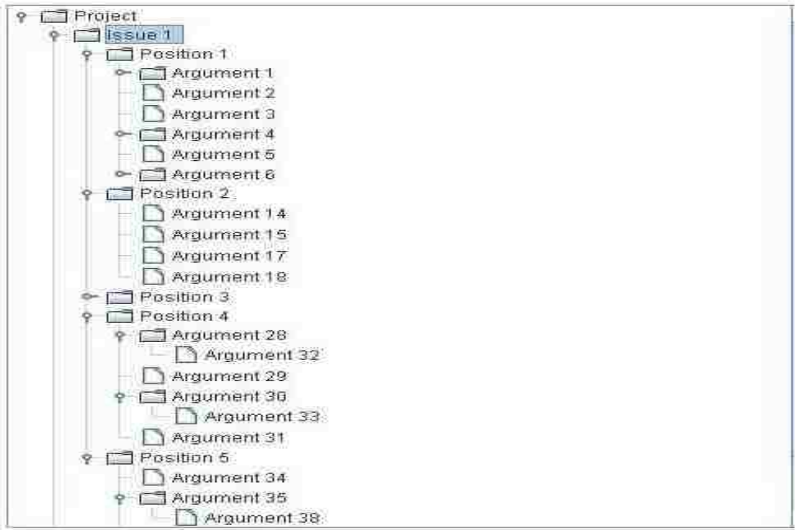


Figure 7.3. Argumentation Tree of Flight Slot Allocation Issue in Air Traffic Management

The argumentation tree is developed by the stakeholders. It evolves as the stakeholders post their arguments under the positions in the tree. We present 5 different figures (Figure 7.4, Figure 7.5, Figure 7.6, Figure 7.7 and Figure 7.8). Each figure represents the argumentation tree of a position. The rectangular boxes at the top of the figure are the positions. The remaining boxes are the arguments in the tree. These arguments are specified by the labels A, B, C, D, and E for positions 1, 2, 3, 4, and 5 respectively.

These arguments also have indexes associated with them. Beneath the label are two boxes. The box on the left indicates the degree of strength of the argument. The box on the right indicates the priority of the stakeholder who posted the argument. The degree of strength is between -1 and +1. The priority of the stakeholder is between 0 and 1. When an argument is posted, the stakeholder should indicate his/her name, the strength of the argument and the priority. Using the mechanism specified in section 2.2.3 in this article, the arguments undergo the inference process. Finally, the weighted summation technique is used to compute the favorability factor of a position.

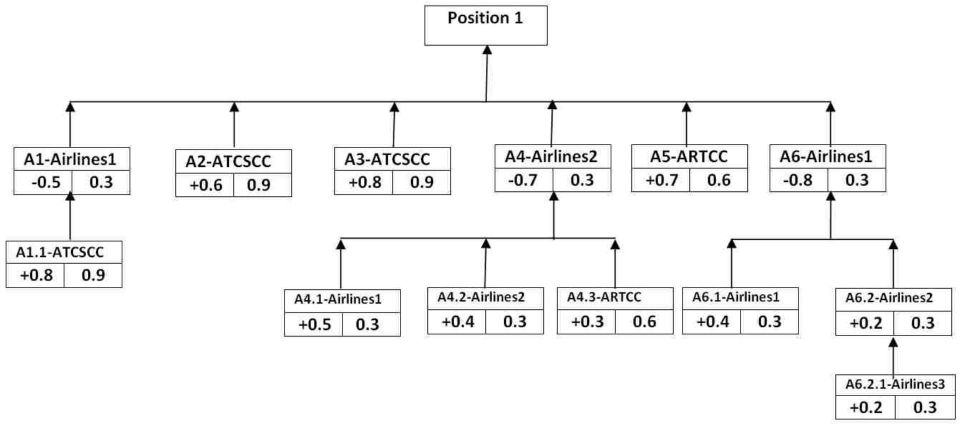


Figure 7.4. Argumentation Tree under Position 1

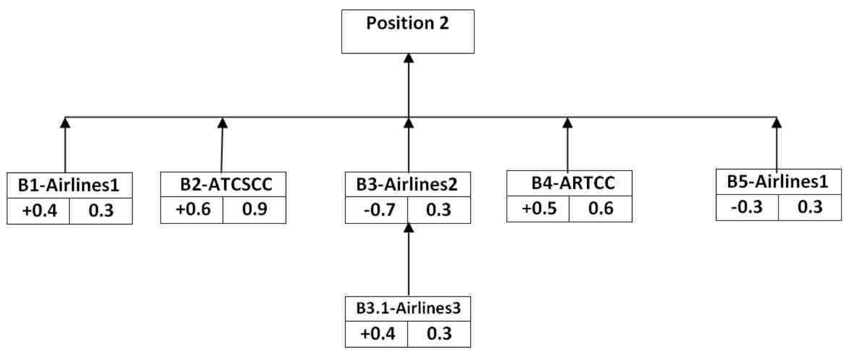


Figure 7.5. Argumentation Tree under Position 2

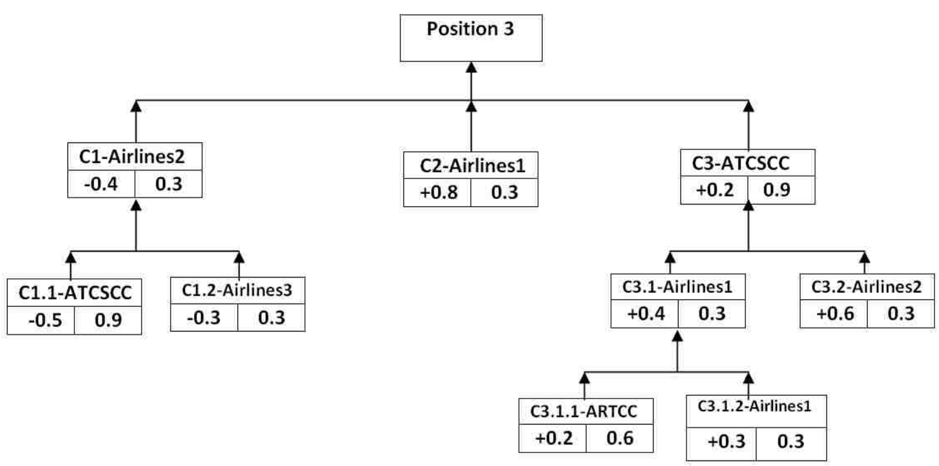


Figure 7.6. Argumentation Tree under Position 3

The detailed arguments of the boxes are as follows:

A1-This alternative has minimum number of flight operations among all the alternatives.

A1.1-It satisfies the range of 45-60 flight operations per hour as suggested.

A2-There is no equity problem in this alternative. Fairness is maintained among the airlines.

A3-This alternative operates 50 flight operations per hour. It is the best one among all the alternatives.

A4-It is difficult to cut down 50% of flights. It would be better if the reduction in operations is by 40%, still the equity is maintained.

A4.1-This idea would be really great, I can reduce my financial loss to a great extent.

A4.2-Passenger delay could be reduced.

A4.3-The sector workload will be relatively more.

A5-Workload in sectors is relatively better with this alternative.

A6-I have my hub in this airport, I need comparatively more flight operations. 50% really affects my economy.

A6.1-Customer satisfaction and reputation of the airlines goes down with this alternative.

A6.2-I do not have any flight operation slots to exchange with you.

A6.2.1-I am running short of flight operation slots. I am not in a position to exchange slots.

B1-This alternative is better than alternative 1. It has more number of flight operations.

B2-This alternative has 55 flight operations per hour. It is a good alternative.

B3-I have many international flights during this time. This alternative doesn't work with me.

B3.1-We can exchange a flight operation slot.

B4-This alternative has more sector work load relatively.

B5-I have my hub in this airport, so I expect more flight operation slots for me.

C1-Equity among the airlines is not maintained.

C1.1-It is same as alternative1 in terms of airlines 2. You get the same number of flight operation slots.

C1.2-Airlines1 is given more priority over airlines 2 and airlines 3.

C2-This alternative drives me to less financial loss relatively.

C3-This alternative operates 60 flights, highest possible value in the given range which is not advised in terms of safety.

C3.1-Fewer number of flight cancellations relatively.

C3.1.1-Workload is high in this alternative.

C3.1.2-Customer satisfaction will be better.

C3.2-Over all passenger delay can be reduced.

D1-Equity among the airlines is maintained.

D1.1-Fewer number of cancellations relatively.

D2-This alternative has 59 flight operations per hour. It satisfies the condition given by the ATCSCC.

D3-This alternative is really great, I can reduce my financial loss to a great extent.

D3.1-Passengers delay could be reduced to a great extent.

D4-This alternative has high workload in the sector.

E1-Equity among airlines is not maintained. This alternative is more favorable to airlines 3.

E2-Passengers delay could be reduced to a great extent.

E2.1-This alternative would be really great, I can reduce my financial loss to a great extent.

E3-This alternative has 59 flight operations per hour. It satisfies the condition given by the ATCSCC.

E4-This alternative has high sector work load.

E5-I have several international flights during this time. This alternative does not work for me.

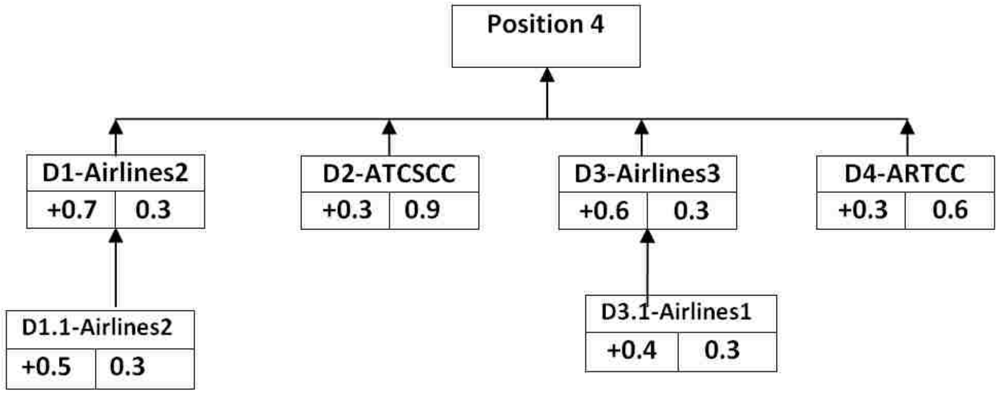


Figure 7.7. Argumentation Tree under Position 4

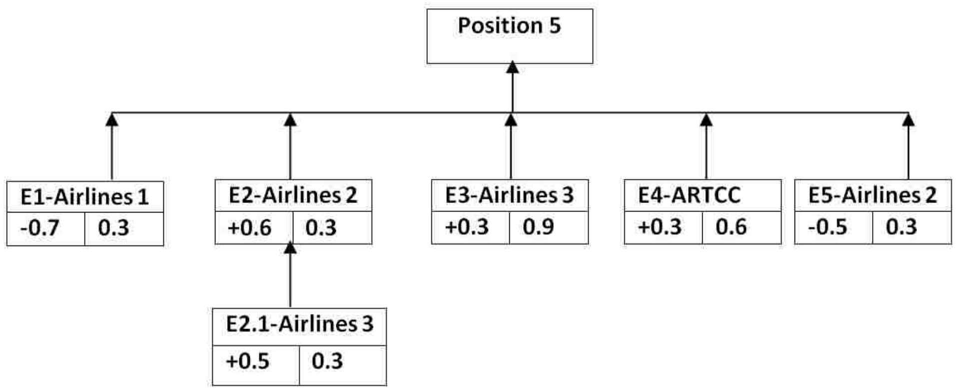


Figure 7.8. Argumentation Tree under Position 5

7.1.4.6 The favorability factor. After the argumentation process, the decision maker selects an issue from the argumentation tree to compute the favorability factor of all positions. Figure 7.9 illustrates the favorability factor of all five positions. Position 4 had the highest favorability factor, indicating position 4 is the most favorable position among the stakeholders. Therefore, position 4 is the winning alternative. Position 2 is the least favorable one among all five positions posted. Reducing flight operations by 40% in all airlines is the most favorable [11, 119]. The position with highest favorability factor follows the constraints provided by the air traffic control system command center (ATCSCC).

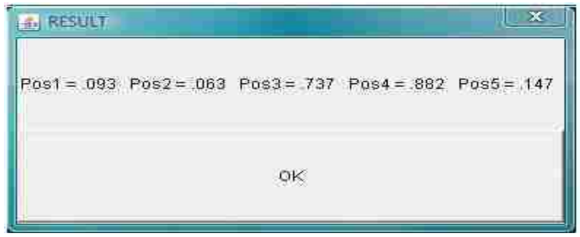


Figure 7.9. Favorability Factor of Positions Produced By the Intelligent Argumentation System

7.1.5. Discussions. The web-based intelligent argumentation facilitates the resolution of conflicts in air traffic management. Web-based intelligent computational argumentation-based conflict resolution improves the exchange of information among the stakeholders who are in geographically distributed locations. When applied to air traffic management, ATCSCC can better understand both the viewpoints and preferences of airlines. This system, when used in air traffic management for resolving conflicts, benefits the stakeholders by bringing in transparency in the decision process.

7.2. COMPARING ARGUMENTATION SYSTEM WITH EMAIL LIST-SERVER FOR COLLABORATIVE DECISION SUPPORT

7.2.1. Introduction. An experiment is conducted to compare the intelligent argumentation system with the email list-server system for collaborative decision support. This experiment was conducted in fall 2010. In this sub-section the experiment details, the case study and the results are presented.

Twenty one students are recruited from the software engineering class to participate in this study. The experiment was conducted for over month using the intelligent argumentation system and an email list-server. The objective of the study was to:

- Evaluate the effectiveness of the intelligent argumentation system and email system for collaborative decision support.
- Measure the effectiveness of collaboration, and participation factor of email system and argumentation system using some metrics that are developed.

- Evaluate the quality of the decision made by the stakeholder groups.

The twenty one recruited students were provided with a software organization case study, and a decision making issue pertaining to that case study. The case study was very concrete and hypothetical by nature. These students played the role of stakeholders in the decision making process. Experiment was conducted from 3rd of November to 14th of December, 2010.

Twenty one students were divided in to two groups, Team A and Team B. Both the teams were provided with the case study and the decision making issue. One team used the intelligent argumentation system and the other used email list-server for the dialogue process to resolve the decision making problem. Surveys forms were provided before, after and during the experiment. Survey was provided to identify the opinion of students about their experience with the tools given to them. The experiment was conducted in four different phases. The framework of the experiment, the case study and the results are explained in the following sub-sections in detail.

7.2.2. Framework. Experiment is started by providing all the stakeholders with the case study details, the issue and the solution alternatives to the issue. The experiment began with a survey. The objective of conducting a survey for all stakeholders was to capture their initial opinion on the given decision making issue. Survey results also tell us the winning alternative through the survey.

Twenty one students were divided in to two groups representing team A and team B. Dividing into teams was performed randomly. Team A had ten students and team B had eleven. In phase 2, team A participated in the decision making process using email list-server and team B used intelligent argumentation system. Both team A and team B were provided one month time to interact with their team members to resolve the decision issue in a collaborative environment.

In phase 3, again the opinions of all twenty one stakeholders on the decision issue are collected using a survey. This was conducted to see the change in their opinion after participating in the discussion process.

In phase 4, the email discussions of team A were provided to team B and the argumentation tree developed by team B was provided to team A. Both team A and team B were provided with some time to read the dialogue process of the other team. Another survey was conducted (survey 3), with some more additional questions about the study. The objective of this survey is to detect and identify change in the opinion of the students after going through the conversations of the other team.

Each phase of the experiment is explained in detail in the following sections. The following sub-section presents the case study.

7.2.3. Case Study. St. Robert's Institute of Science and Technology was founded in the year 1930 and offers degrees and courses in various fields of engineering. 5000 students are currently enrolled as full-time students in this University. There are about 107 instructors, with 45 staff members working in different departments including with registrar office, library, cashier's office and so forth.

The responsibility of registrar's office staff is to help students in enrolling courses, dropping and swapping courses. The responsibility of employees in cashier's office is to manage the financial transactions concerned with the students. As the students enroll courses in a semester, based on their enrollment the cashier's office staff is responsible to collect tuition fees and other activities fees such as insurance and many more.

With very wide range of courses offered in each department for graduate and undergraduate students. It has been very difficult for the administrative staff to manage the student records. Students had a wide range of courses to select with very limited number of seating in each class. There is a tough competition in the enrollment process of the courses in each semester. Presently, the registrar office staff is using a DB2 application, in enrollment process, where the administrative staff works with the database. It is difficult for the staff to work with this application. The staff needs to run queries for each and every student request. A student needs to physically appear in the registrar office and fill out the course registration form. Based on the student form details, administrative staff runs query and registers a class for the student. It is challenging and tiring for the administrative staff. Sometimes students need to wait in the queue for long hours to finish their course registration process. Both the students and the administrative staff follow the same procedure to drop a class or swap a class. The instructors had to fill up forms in order to know the number of students enrolled in their class. Presently, the students, instructors and the administrative staff are having trouble with the enrollment procedures. Because of this problem, the University has come to a conclusion that, they need to consult Peribot technologies to help them building a software application. This software should help the University students, staff and faculty. In the desired system, all the students, instructors and staff including registrar's office staff and cashier's office staff can access the software application over the Web. Each and every user is given login credentials. Using their log-in credentials, one can log-in and perform the actions.

Peribot Technologies, a division of Peribot Limited, is a software company based in Los Angeles, California. Peribot Technologies is an information, communications and technology company providing good integrated business applications, and information technology and process solutions on a global level infrastructure.

A thorough discussion was carried out between the requirements team from the University and the core team from the Peribot technologies. Software requirements documentation was then generated by the Peribot team. Now, the Peribot technologies team has to select software process model they need to adopt to develop this software.

Issue - Selecting software development process model for developing the software that is needed by the University?

Positions – Students were provided with the decision making issue and the positions (alternatives). Both the issue and the positions are built around the case study. In this experiment we have three positions:

1). Waterfall Model

2). Agile Process Model

3). Unified Process Model

Twenty one students from the software engineering class played the role of software developers from the Peribot technologies to resolve the decision issue. The decision issue and alternatives are provided to all stakeholders in all three surveys and also for group discussion by email system and argumentation system. The complete experiment was built around this case study, and we have empirically evaluated the results.

7.2.3.1 Phase 1. The experiment began with a survey. Survey 1 was conducted starting from November 3rd to November 6th, 2010. All twenty one students participated in this phase. Eleven students expressed that agile process model would best suit for the given case study, seven supported waterfall model and three students supported unified process model. The results of survey 1 are also presented in the following figure (Figure 7.10).

In the first survey (survey 1), one of the important questions was the rationale behind a stakeholder supporting an alternative. With this question, we understood the perspective of the stakeholders. This defined the criteria set assumed by the stakeholders.

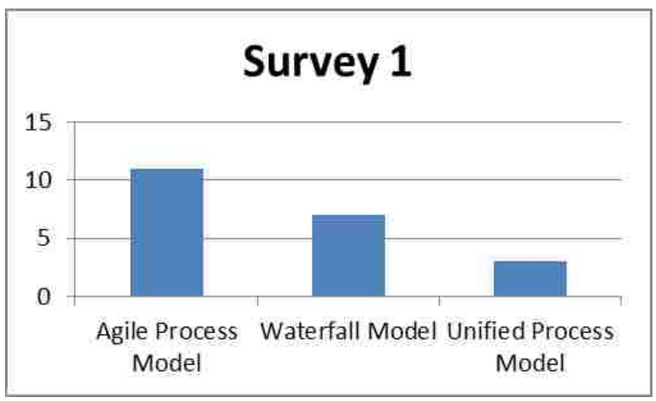


Figure 7.10. Support for an Alternative in the First Survey

7.2.3.2 Phase 2. This section presents how both team A and team B used the email system and the argumentation system respectively for collaborative decision making. Stakeholders exchanged posts in both email and argumentation system from November 7th to December 5th, 2010. The ten stakeholders were added to a list-server and the name of the list-server was distributed to everyone in the team. Anyone in team A can post emails to that list-server. Totally 42 emails have been circulated in the group of ten stakeholders under nine different threads. Out of these 42 emails, 37 were exchanged by the team and the rest were by the mediator. The discussion between the stakeholders was about the given issue and alternatives. They exchanged emails and arrived at a conclusion. The participation of the stakeholders in the email system was low. From the email conversations we identified that, the unified process model received highest support, waterfall model was next highest supported and the support for the agile process model was very low. The email group had considered twenty-six different criterions during collaborative decision making process. Figure 7.11 presents the contribution made by each stakeholder in team A.

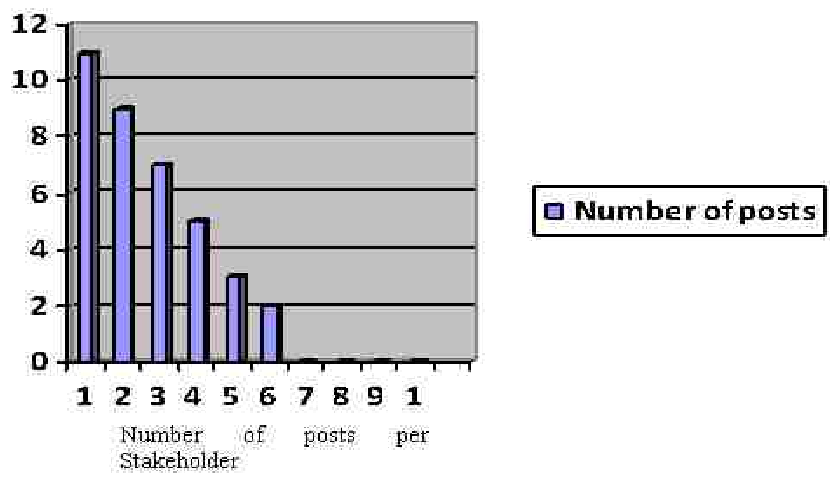


Figure 7.11. Contribution of Each Stakeholder in Team A

Team B used intelligent argumentation system. In argumentation system, there are eleven students who built argumentation tree with thirty arguments and eight evidences. The participation level was low. The intelligent argumentation system allows stakeholders to argue among them and assists them in decision support. The system computes the favorability factor of each position and present position with highest favorability. The system computed the favorability factor of the given three positions in the argumentation tree. Higher the favorability factor value is the more favorable the position is. Table 7.4 presents the favorability factor of all three positions. Waterfall model was the position with highest favorability value. See Figure 7.12 for the argumentation tree built by team B.

Table 7.4. Favorability Factor of Each Alternative Computed by the Argumentation System

Position	Favorability factor
Agile Process Model	2.265
Waterfall Model	5.226
Unified Process Model	.494

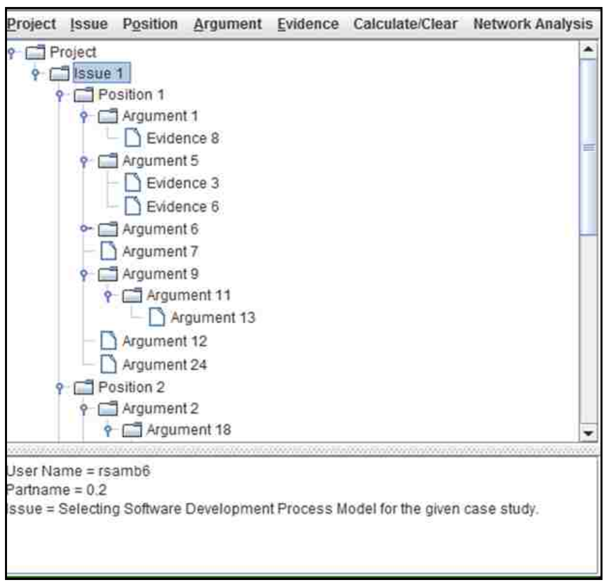


Figure 7.12. Argumentation Tree Developed by Team B

In team B, the waterfall model was highly supported by the stakeholders, followed by agile process model. The support for unified process model was low. Figure 7.13 illustrates the contribution made by each stakeholder in team B using the intelligent argumentation system.

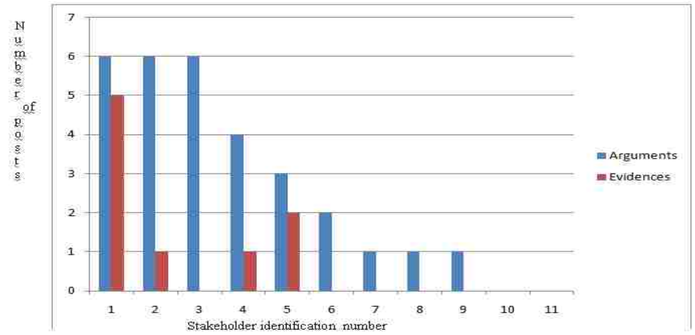


Figure 7.13. Contribution of Each Stakeholder in Argumentation System

Table 7.5. Depth of the Argumentation Tree

Depth of the argument tree	Percentage of arguments	Percentage of evidences
1	63.3%	0%
2	33.3%	80%
3	3.33%	10%
4	0%	10%

Table 7.5 presents the percentage of arguments and evidences in the argumentation tree (Figure 7.12). Team B considered 29 different criterions during collaborative decision making among them.

7.2.3.3 Phase 3. The second survey was conducted from December 6th, 2010 to December 9th, 2010. Sixteen students participated in survey 2. The results of survey 2 are presented in Figure 7.14. Out of the sixteen stakeholders six supported agile process model, five supported waterfall model and five stakeholders supported unified process model.

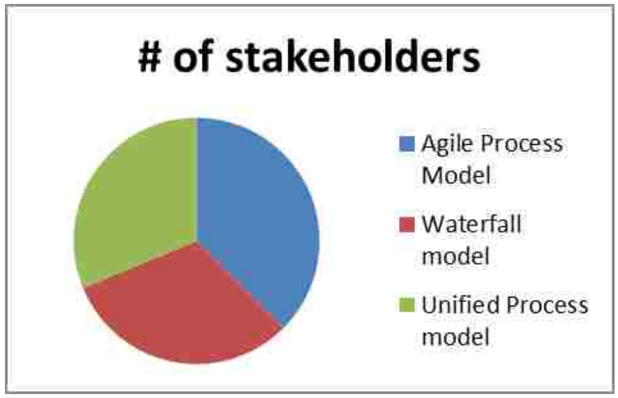


Figure 7.14. Support of an Alternative in the First Survey

From survey 2 we identified that, six stakeholders reaffirmed their opinion, seven stakeholders strengthened their opinion, and three stakeholders' opinion was remained unchanged. No stakeholder's opinion was weakened during the process of discussion in phase 2. We can conclude that out of sixteen stakeholders, who have participated, thirteen stakeholders' opinion has been changed and three stakeholder's opinion remained unchanged. We understand that the process of collective intelligence and knowledge exchange helped people change their mind.

After the second survey, team A was given access to view the argumentation tree built by team B and team B was provided with the emails exchanged by team A. We provided students with some time to go through conversations, and then we conducted survey 3. The results of survey 3 are presented in the following section.

7.2.3.4 Phase 4. The third survey was conducted from December 9th to December 13th, 2010 and fourteen stakeholders out of twenty one participated. Seven were from team A and seven were from team B. Out of fourteen stakeholders who participated in the survey, five stakeholders supported agile process model, five stakeholders supported waterfall model and four opted unified process model. See Figure 7.15 for the third survey results.

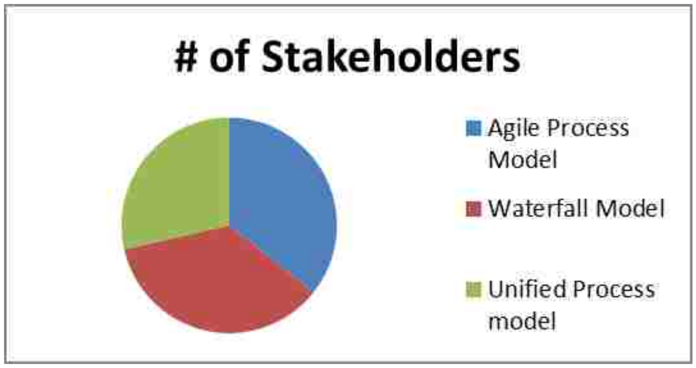


Figure 7.15. Support of an Alternative by Stakeholders in the Third Survey

Out of seven people from team A who participated in the third survey, six stakeholders have gone through the argumentation tree built by team B. Out of seven people from team B, six stakeholders have gone through the email conversations exchanged by team A. In survey 3, six stakeholders have agreed that argumentation system is a better tool in achieving consensus in a group than a email list-server. Six stakeholders agreed that, the information in the argumentation system is more structured, many stakeholders however, not answered this question. Seven stakeholders supported argumentation tool is better in helping in comprehending the rationale of the decision. In survey 3, the stakeholders have considered twenty two different criterion for decision making.

7.2.4. Results and Analysis. The criterion set considered by team B during the decision making process was stronger when compared with the criterion set considered by team A. In phase 1, each individual stakeholder has considered some criterion for decision making. In several cases, some of them have considered a similar set of criterion. After participating in the collaborative decision making process, several stakeholders considered many other criteria. This was evident from the second survey. A group of people can definitely produce more when they work collaboratively. But, the web-based collaboration tool that a group is using also has an impact.

The intelligent argumentation system is more advanced than email system in organizing the posts. It helps in capturing the rationale of the stakeholders and also helps achieve consensus in the group. Better organization of posts also helps the stakeholders in better understanding and comprehending the posts of other stakeholders. When an argument is posted, a stakeholder can come back to see his/her arguments and other arguments that either support them or attack them.

In email list-server, as more and more mails are posted in the same thread it is very difficult to track the conversation and the criterion or sub-criterion in the discussion might change very quickly. Some information in a post might be lost. There is a very little scope for argumentation and some stakeholders may be unheard. Scalability is an important aspect in an email list-server for collaborative decision process. If huge number of stakeholders participate in the argumentation process using an email system, it becomes difficult to understand which stakeholder is responding to whom.

Klein et al. [34] conducted an experiment with argumentation system with a group as big as 200 students. In spring – 2010, Satyavolu et al. [8] conducted experiment on the intelligent argumentation system with twenty-five stakeholders. The structure and representation of arguments in the tree makes an argumentation system unique from other mass communication tools such as email, Weblog, forums. In addition the intelligent argumentation system has the decision support ability, which is built using the fuzzy systems.

We present some metrics here that help us understand and compare an email list-server and the intelligent argumentation system for collaboration.

Quality of collaboration is computed using the number of stakeholders actively participated in a group and the total number of stakeholders registered in that group. This value can range between zero and one.

Quality of Collaboration = (# of stakeholders participating actively)/(# of stakeholders registered in the group)

Quality of Collaboration for the group that used email system (team A) was 0.6 and for the team B was 0.81.

Average number of posts posted by a stakeholder is another metric to understand the activity in a group. It is computed by using the total number of posts in a group and the total number of stakeholders registered in that group.

Average # of posts by stakeholder = (Total number of posts) / (Total number of stakeholders)

The average number of posts posted by a stakeholder in team A is 3.7 and in team B is 3.63.

Table 7.6. Individual Stakeholder Contributions

Stakeholder Id	Group	Contribution to collaboration
1	Team A	0.29
2	Team A	0.24
3	Team A	0.189
4	Team A	0.135
5	Team A	0.08
6	Team A	0.05
7	Team A	0
8	Team A	0
9	Team A	0
10	Team A	0
11	Team B	0.275
12	Team B	0.175
13	Team B	0.15
14	Team B	0.125
15	Team B	0.125
16	Team B	0.05
17	Team B	0.025
18	Team B	0.025
19	Team B	0.025
20	Team B	0
21	Team B	0

Individual stakeholders' contribution to collaboration is another interesting metric that is computed using the total number of posts posted by a stakeholder and the total number of posts posted by the team. Table 7.6 presents each stakeholder's contribution towards the collaboration.

Individual stakeholder contributions = (# of posts of a participant)/ (Total number of arguments/posts)

Some additional metrics for the email list-server are also presented here.

1. Ration of argumentation-related emails to non-argumentation emails = (16) / (37) = 0.432. Out of thirty seven emails exchanged in the group, only sixteen of them were argumentation based and the rest were based on the opinion of the stakeholders.
2. Average length of threads in email-based argumentation = 37 / 4 = 9.25 (Four threads)

Table 7.7 illustrates the number of posts exchanged by team A and team B during the discussion process in phase 2.

Table 7.7. Number of Posts Exchanged by Team A and Team B

Posts during the discussion	E-mail System	Argumentation System
Arguments based posts	16	30
Evidences based posts	1	10
Total # of posts	37	40

Some observations were made during the study. It was challenging for stakeholders to come to a conclusion using an email list-server. They tend to go for voting which is similar in a way with survey system. After phase 2, the discussion process, in the second survey some stakeholders changed their support for a position from survey 1. The discussion process in phase 2 has helped stakeholders. We also realized that as people have been using email system for a long time, it was easier for them to participate. In case of an argumentation system, people had to learn to post the arguments supporting or attacking other arguments or an alternative.

The quality of the decision directly depends on the criteria set developed during the discussion by the team. The criterion set identified in phase 2 in the discussion process is much larger and stronger. The criterion set considered by the stakeholders in survey 2 and survey 3 were much stronger than survey 1.

Argumentation system allows stakeholders to argue, which is central to the collaborative decision making. This was not possible in the email system. Intelligent argumentation system is advanced in terms of decision support ability.

8. CONCLUSION

In a large argumentation tree, analyzing arguments is challenging. Four research challenges were identified and addressed to analyze argumentation trees. First, a method was proposed to identify polarization groups, and leaders in the argumentation process. Later, a novel approach was developed to quantify stakeholders' degree of membership in multiple polarization groups. These polarization assessment frameworks help in better understanding polarization groups and polarization group formation process. Results from these frameworks also help in identifying stakeholder who is playing important role in polarization groups.

A method was developed to assess the collective opinion of stakeholders in a group, on each individual argument in an argumentation tree and cluster the arguments based on the collective determination scores. This framework produces clusters of arguments with collective support and collective attack. Results produced from this framework helps in understanding the collective perception of the group on every argument in a tree.

Finally, a framework was developed to identify outlier opinions in argumentation trees, from both individual and collective viewpoint. Using the results from outlier opinion framework one can understand how different are the outlier opinions from inlier opinions in an argumentation tree, from both the perspectives.

Evaluations of the proposed methods were also presented. Empirical results are consistent with the social dynamics in the decision making group with higher accuracy.

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VITA

Ravi Santosh Arvapally was born in Hyderabad, Andhra Pradesh, India. He received PhD from Missouri University of Science and Technology, Rolla in December 2013 and Bachelor's degree in computer science from Jawaharlal Nehru Technological University, Hyderabad in May 2008. He received Dean's International Computing and Engineering award (DICE) at University of Missouri, Kansas city (UMKC) for Master's degree in computer science in FALL 2008. He started his Master's at UMKC and then transferred to Missouri University of Science and Technology, Rolla (MST) in SPRING 2009 to start his PhD in the area of social computing and software engineering. At Missouri S&T, Ravi worked as a graduate research assistant for McDonnell Douglas Foundation Software Engineering Laboratory and grader for several software engineering courses in computer science department.

Ravi has received IEEE Richard E Merwin scholarship, IEEE St. Louis outstanding student member award, and computer science department ambassador award at MST. In 2012, he served as the student ambassador for IEEE computer society in Region 5. Ravi served as financial committee chair, treasurer and student chair of IEEE computer society student branch at MST. Ravi received support for his research from Intelligent Systems Center (ISC) and National University Transportation Center (NUTC) at Missouri S&T. His research interests include intelligent argumentation, collaborative decision support, and social computing.