Optimizing Social Consensus: The Impact of Agent Selection and Topic Strategy on Time to Reach Agreement

Johannes S Vorster[1] [a] and Louise Leenen[1,2] [b]
[1]*Department of Computer Science, University of Western Cape, South Africa*
[2]*CAIR, South Africa*

Keywords: Consensus, Consensus Simulation, Stochastic Simulation, Synchronization, Multi-Agent Simulation.

Abstract: In the rapidly evolving landscape of organizational structures and project management, achieving timely consensus among team members is crucial for maintaining agility and responsiveness. During the consensus formation process, team members has the choice of who to talk to in an attempt to consolidate views on a topic. In this paper we ask the question, to what extent do strategies for selecting team members affect the speed of consensus formation? Similarly, once two team members engage in conversations on a specific set of topics, the question we ask is, to what extent do different strategies for selecting the topics for discussion affect the time to reach consensus within multi-agent systems. By simulating various strategies, we identify methods that optimize consensus speed, specifically highlighting the benefits of prioritizing unaligned agents and addressing contentious topics early in the process. Our findings reveal that these strategies significantly enhance consensus efficiency, while approaches focusing on aligning with similar views tend to prolong the process. Additionally, we observe that the initial distribution of agent views, provided the standard deviation is constant, has negligible effects on consensus time, suggesting that diversity of opinion is more critical than specific distribution patterns. These insights offer practical implications for improving decision-making processes in organizational and project contexts.

1 INTRODUCTION

1.1 Organizational Context

As technological innovation accelerates, businesses must adapt their organizational structures and project delivery methods to remain agile and responsive in a constantly changing environment. Over the past two decades, the evolution of organizational structures and project strategies has become a major topic in both academia and industry. This discussion is largely driven by technology companies navigating the complex interplay of rapid technological advancements, shifting competitive landscapes, and evolving customer expectations (Reagans et al., 2016; Keupp et al., 2012; Chang and Harrington, 2000). Evidence suggests that lateral structures and well-connected networks offer greater economic value, reflected in faster project delivery and reduced resource use, leading to better investment returns (Will et al., 2019). However, project complexity often hampers consensus-building among team members, causing delays and failures (Al-Ahmad et al., 2009; Whitney and Daniels, 2013; Kian et al., 2016; Waheeb and Andersen, 2022).

1.2 Consensus Models

Consensus formation in Multi-Agent Systems (MAS) is a multifaceted challenge, intersecting fields such as social sciences, economics, and computational modeling. Traditional methods like the Delphi process have been complemented by computational models that simulate consensus dynamics (Yan et al., 2017). These models draw from social science research on crowd behavior and voter dynamics (Dunbar, 1998; Stocker et al., 2001; Leishman et al., 2009). In MAS, algorithms are designed for high-speed applications, reflecting the need for rapid consensus in dynamic environments (Amirkhani and Barshooi, 2022).

[a] https://orcid.org/0000-0001-6452-4186
[b] https://orcid.org/0000-0002-9212-550X

Vorster, J. S. and Leenen, L.
Optimizing Social Consensus: The Impact of Agent Selection and Topic Strategy on Time to Reach Agreement.
DOI: 10.5220/0013650900003970
In *Proceedings of the 15th International Conference on Simulation and Modeling Methodologies, Technologies and Applications (SIMULTECH 2025)*, pages 135-144
ISBN: 978-989-758-759-7; ISSN: 2184-2841

1.3 Social Settings

The topology and connectivity of social networks significantly influence opinion dynamics and consensus formation. Models such as Erdős-Rènyi, Watts-Strogatz, and Barabási-Albert provide insights into how network structures affect the speed and nature of consensus formation (Erdős et al., 1960; Watts and Strogatz, 1998; Barabási et al., 2000). These models highlight the importance of network design in facilitating or hindering consensus, with complete networks often leading to the fastest agreement (Michalski et al., 2022).

1.4 Subversive Agents

The role of subversive agents in consensus processes has been explored across various domains, revealing that even a small committed minority can significantly influence group dynamics (Xie et al., 2011; Iacopini et al., 2022). In project teams, subversive agents can delay consensus by introducing conflicting views, underscoring the need for effective management of dissent and conflict (Vorster and Leenen, 2023b).

1.5 Organizational Structure

Organizational structure plays a critical role in consensus formation. Polyarchies, characterized by fully connected networks, facilitate quicker consensus compared to hierarchical or hybrid structures (Will et al., 2019; Vorster and Leenen, 2024a). The choice of structure impacts not only the speed of decision-making but also the quality of outcomes, particularly in innovation and project selection (Sáenz-Royo and Lozano-Rojo, 2023).

1.6 Our Earlier Work and Motivation for this Paper

Our previous research has extensively explored the dynamics of consensus formation within organizational settings, focusing on various factors that influence these processes. In Vorster and Leenen (2023a), we introduced a simulator designed to investigate consensus within organizations, emphasizing the role of organizational structure, team dynamics, and artefacts. That study highlighted that for a fixed problem size, consensus could be achieved within a maximum time frame, independent of the number of agents involved.

Building on that, Vorster and Leenen (2023b) examined the impact of subversive agents on consensus-seeking processes. That work revealed how subversive agents, whether engaging in industrial espionage or acting as disgruntled employees, could subtly delay consensus by influencing team dynamics without raising suspicions.

Furthering this exploration, Vorster and Leenen (2024b) delved into the influence of subversive agents on project teams, demonstrating that even a small minority of such agents could significantly extend the time to reach consensus. This study underscored the potent influence of subversive agents in shaping decision outcomes.

In Vorster and Leenen (2024c), we investigated the determinants of consensus processes, such as group size and the role of artefacts. The study found that artefacts significantly reduce consensus time, emphasizing their importance in streamlining communication and collaboration within teams.

Additionally, Vorster and Leenen (2024a) explored the effectiveness of artefacts and documentation in facilitating consensus. That research highlighted that while polyarchies are efficient at consensus formation, smaller teams with well-structured artefacts can achieve similar efficiency, particularly in larger organizations where intra-team communication may cause delays.

These studies collectively contribute to a nuanced understanding of the factors affecting consensus formation, providing valuable insights for optimizing decision-making processes in organizational contexts.

This paper investigates the impact of agent selection strategies and topic prioritization on time to reach consensus. By examining different strategies for selecting discussion topics and agent alignment, we aim to identify methods that optimize consensus speed. Our findings suggest that prioritizing unaligned agents and discussing topics with the most differences in views *first* significantly improves consensus efficiency. This research contributes to the broader understanding of consensus dynamics in organizational and computational contexts, offering practical insights for enhancing decision-making processes.

1.7 This Work: Agent and Topic Selection Strategies

In this paper we want to investigate two aspects and the interaction between them; agent selection and topic selection.

In initial studies mentioned above, agents interact with other agents at random and do not have a strategy for how to select other agents. In this paper we investigate two main strategies (a) prioritize selecting

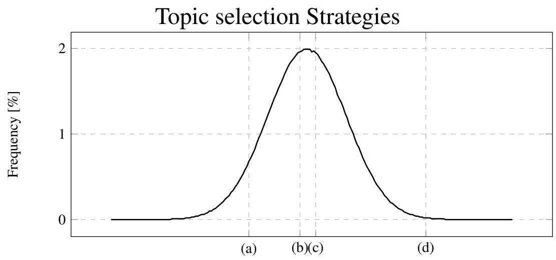

Figure 1: Topic selection strategies: (a) closest same side, (b) furthest, same side, (c) closest, opposite side, and (d) furthest, opposite side.

agents that have closely aligned views, and (b) prioritize selecting agents with conflicting views.

It can be argued that following the first strategy is similar to first building a core of support, establishing a large group of agents with a particular view to portray that view to other agents.

On the other hand, the second strategy, to prioritize agents with the furthest views are more aligned with a philosophy of trying to contain opposing views and thus restrict the spread of these opposing views as quickly as possible.

We are interested to see, using our simulation approach, what the effect of these two strategies are on the time to reach consensus in a large group where it is critical that consensus is reached, such as in project execution (as opposed to social constructs such as voter views).

An orthogonal aspect of investigation is topic selection; is it better to (a) focus on similar topic, eliminating differences quickly and establishing a core of mutual topics, or (b) focus on trying to address the topics with highest difference in views first.

A second way to look at this variable is for an agent to select topics based on the relative position to the group view. Lets say agent i has a view to the left (or right) of the group's view on topic k. Would it be better to first select topics where agent j is on the same side of the issue or is it better to discuss opposing topics first? Here we identify and investigate four strategies: (a) prioritise topics on the same side of the issue and topics closest to the agents views first (Close, same side topics); (b) prioritize topics on the same side of the issue but with the biggest difference in views first (Furthest, same side topics); (c) opposite side but closest to the agents own view (Closest, opposite view); and (d) opposite view and furthest away (Furthest, opposite view), see Figure 1 where agent i has a view close to that of (a).

Here, option (c) aims to pull agents with opposing views but close to the median view over the line to 'our side'. Strategy (b) tries to prevent this from happening to agents on 'our team'. Strategy (d) aims to address the 'radicals' on the opposite side first and strategy (a) aims to consolidate and build out the core of support.

Our approach is to set up two sets; one with nine experiments (three options on each axis of a two-variable matrix). Axis one is the agent selection strategy: Random strategy, agents with highest difference in views first, and agents with lowest difference in views first. On the second axis is the topic selection strategy, with similar three options. And the other set with twelve experiments, where the second axis covers the four options mentioned above.

2 METHODOLOGY AND TERMINOLOGY

This section outlines the methodology and terminology used in our study, focusing on the simulation setup, agent interactions, and consensus measurement. A detailed discussion of topics related to the simulation and simulator can be found in Vorster and Leenen (2023a).

2.1 Teams and Topics

The simulation involves two teams: the specification team (team a) and the implementation team (team b). Team a consists of ${}_aN$ agents, and team b consists of ${}_bN$ agents, with ${}_aN \ll {}_bN$. Each agent tracks a number of topics, with team a considering ${}_a\mathcal{B}^{\max}$ topics and team b considering ${}_b\mathcal{B}^{\max}$ topics. The first ${}_a\mathcal{B}^{\max}$ topics are common to both teams, requiring consensus between both teams.

2.2 Artefacts

Topics are encoded in specification artefacts, which map one-to-one with the topics tracked by team a. The specification contains ${}_a\mathcal{C}^{\max}$ topics. If an artefact contains fewer topics than discussed by agents (${}_a\mathcal{C}^{\max} < {}_a\mathcal{B}^{\max}$), the first ${}_a\mathcal{C}^{\max}$ topics coincide with the artefact's topics, allowing for the modelling of incomplete artefacts.

2.3 Agent Connectivity and Meetings

Agents interact based on a connectivity graph modelled as a directed graph. Each agent can only meet with directly connected agents. Meetings last 30 minutes, allowing up to 16 meetings per day. The number of topics discussed per meeting is determined stochastically, ranging from one to ten. Outcomes for each topic include compromise consensus, one agent convincing the other, or vice versa. The pseudo-Python code for meetings between agents i and j is:

```
random.shuffle(topics)
issuesToDiscuss=randint(1,11)
for k in topics:
  if agent[i].view[k]==agent[j].view[k]:
    continue
  rnd = randint(0,3)
  if (rnd==0):
    val = int((agent[i].view[k]
       + agent[j].view[k]))/2.0)
    agent[i].view[k]=agent[j].view[k]=val
  if (rnd==1):
    agent[j].view[k] = agent[i].view[k]
  if (rnd==2):
    agent[i].view[k] = agent[j].view[k]
  issuesToDiscuss-=1#
  if issuesToDiscuss<=0:
    break
```

2.4 Working on Artefacts

Agents can interact with artefacts within a 30-minute time-slot, selecting a random number of topics, from one to ten, where disagreement exists between agent's views and the artefacts position. Outcomes include partial or full internalization of the artefact's view or modifying the artefact to reflect the agent's view.

2.5 Measuring Consensus

Consensus is measured using absolute differences between views (b) on topics (k). For agents i and j, and artefacts p, the consensus measure for a specific topic (k) is:

$$u_{ij}^k = \delta_{ij}|b_i^k - b_j^k|$$

$$u_{ip}^k = \delta_{ip}|b_i^k - c_p^k|$$

where δ_{ij} is a coefficient of understanding each other, and is taken as $\delta_{ij} = 1$ here. The overall consensus for an agent i over all agents (I_v) and all artefacts (I_A) for a specific topic k is:

$$u_i^k = \sum_{j \in I_v} \delta_{ij}|b_i^k - b_j^k| + \sum_{p \in I_A} \delta_{ip}|b_i^k - c_p^k|$$

The total difference in views between two agents on all topics is given by

$$u_{ij} = \sum_{k=1}^{\mathcal{B}^{\max}} \delta_{ij}|b_i^k - b_j^k| \tag{1}$$

The total consensus across all agents and artefacts is:

$$u = \sum_{i \in I_v} \sum_{j \in I_v} \sum_{k=1}^{\mathcal{B}^{\max}} \delta_{ij}|b_i^k - b_j^k| + \sum_{i \in I_v} \sum_{p \in I_A} \sum_{k=1}^{C^{\max}} \delta_{ip}|b_i^k - c_p^k|$$

This measure (u) and its log is what will be used to measure the level and extent to which a group has reached consensus.

2.6 Time and Effort to Reach Consensus

Agents record their actions in a diary. The effort $e^{\max}$ to reach consensus is the sum of all actions taken:

$$e^{\max} = \sum_{t=1}^{t^{max}} \sum_{i=1}^{N} busy(d_i^t)$$

where $busy(d_i^t) = 1$ if an action is taken, and 0 otherwise. The simulation stops, after t^{max} steps, when no further actions are taken. We are interested in t^{max} (averaged over may simulations) for the various scenarios under investigation.

2.7 Meeting Efficiency

Meeting efficiency is measured by the average number of topics discussed per meeting. If $\bar{z}(t)$ is the observed average and $\bar{z}^{max}$ is the maximum expected, efficiency at time t is:

$$e(t) = \frac{\bar{z}(t)}{\bar{z}^{max}}$$

2.8 Strategy Notation

There are two dimensions to the strategy that an agent (i) can follow. Firstly the selection of agents to meet with, which we can denote as Strategy (Agents=far) for the the strategy of prioritizing agents with overall views that are far from the current agent's views, that is, agents (j) where the consensus measure (u_{ij}, eq. (1)) is relatively large. Three strategies are considered namely Strategy (Agents=far), Strategy (Agents=near), and Strategy (Agents=random).

Similarly and independently from the agent selection strategy an agent can also have a strategy for the topics that will be discussed in a meeting. Such strategies can be denoted with Strategy (topics=random), Strategy (topics=Far), and Strategy (topics=Near) for the three strategies we are considering, where topics=Far denotes a strategy where agents will prioritize topics k where $|b_i^k - b_j^k|$ is large relative to other topics.

An agent's overall strategy will consist of having a strategy for agent selection and a strategy for topic

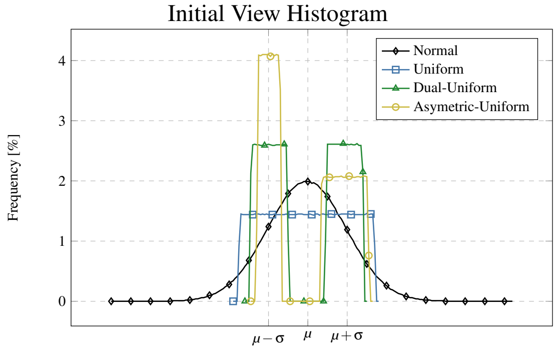

Figure 2: The distributions used for initial views are: Normal, Uniform, Dual-Uniform, and Asymetric-Uniform as shown in the figure. Each distribution is carefully selected so that σ=constant=100, for all distributions.

selection, and the combination can therefore be indicated using the same notation, for example Strategy (agents=random, topics=random).

Next, we move on to the topic of strategies for agent selection and topic selection. Equation (1) provide a mechanism for an agent to calculate a consensus measure between it and another agent, and thus an agent can select the agent with the smallest or largest such value in order to implement the two strategies (a) best aligned agent first, and (b) furthest aligned agent first.

Similarly agent i can find a topic k, such that $|b_i^k - b_i^m|$ is the smallest (non-zero) value among the topics $m \in \{1 \text{ to } \mathcal{B}^{\max}\}$ for which they are not in agreement.

2.9 Mathematical Model Summary

Key concepts include:

- b_i^k: The view that agent i has on a specific topic k.
- u_i^k: Consensus on a specific topic k for agent i.
- u_{ij}: Consensus between two agents i and j on all topics.
- u: Overall consensus measure.
- t^{max}: Time to reach consensus.
- e^{max}: Effort to reach consensus.
- Strategy (agents=X, topics=Y): A strategy that prioritizes agents using an agent selection strategy X based on the consensus measure u_{ij}, and a strategy Y for selecting topics to discuss within meetings based on the measure $|b_i^k - b_i^m|$.

This methodology provides a framework for analysing consensus dynamics in multi-agent systems.

3 SCENARIO CONFIGURATIONS

Agents are initialized with random views on each of the topics using a specific distribution. Currently Normal, Uniform, Dual-Uniform, and Asymmetric-Uniform are supported, see Figure 2.

A simulation consists of agents meeting in 30 minute sessions where they discuss topics according the the rules explained above. This continue until all agents are satisfied that they have reached consensus on all topics with all other agents in their connectivity network. The number of time-steps that it takes to reach this state is noted. The exponential decrease in the consensus measure (u) can be seen as one of the grey plots in Figure 3. Over many such iterations averages and standard deviations can be computed, as shown in the figure.

Although not the primary focus of this study, Vorster and Leenen (2023a), pointed out that the consensus process may be dependent on the distribution of initial views and in that work the mathematical model was worked out based on a Normal distribution of initial views. However, the question remained open and in the first part of this work we want to address it by modelling various initial distributions, see Figure 2. Through that work, it was assumed that the consensus process, in particular how long it takes, is dependent on the *standard deviation* of the distribution in the absense of other information. Here we measure the time to reach consensus for Normal, Uniform, Dual-Uniform, and Asymmetric-Uniform as shown in the future. In all these distributions we take care to use the same mean and sigma in the initial view distributions.

For example to correctly compute the distribution of the Asymmetric-Uniform distribution, we selected the distribution width of the left portion (50 in this case) and compute what the right-hand portion should be to give the correct sigma ($\sigma = 100$). To ensure we have not made mistakes in the mathematical calculations or in the Python implementation we simulated stochastically two million distribution calculations to ensure correctness, with results Normal ($\sigma = 100.05$, n=2M), Uniform ($\sigma = 100.00$, n=2M), Dual-Uniform ($\sigma = 99.98$, n=2M), Asymmetric-Uniform ($\sigma = 100.03$, n=2M).

The outcome of these simulations are shown in Figure 4. The effect of initial views are negligible as can be seen from the (bottom) graphs showing the difference between the outcome of these distributions relative to the Normal distribution. This is somewhat of a surprising results since it then implies that the time to reach consensus is independent of the distribution of initial views, but only dependent on the

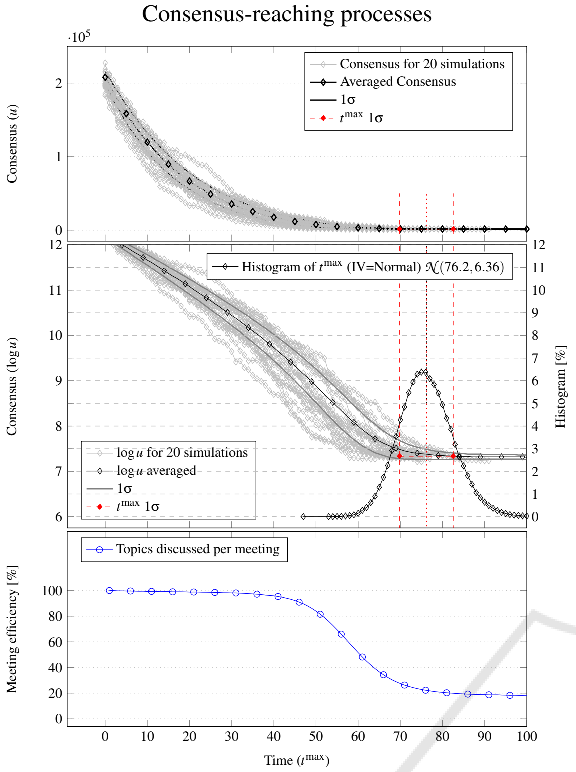

Figure 3: (Top) Various simulations of the 10-group showing the consensus measure (u) over time. (Middle) The same data as in top graph, but now using $\log_e$(consensus). Histogram of the time it takes to reach consensus over many such runs ($\mu = 76.2$, $\sigma = 6.36$, n=200000). (Bottom) Meeting effectiveness graphs for the two groups.

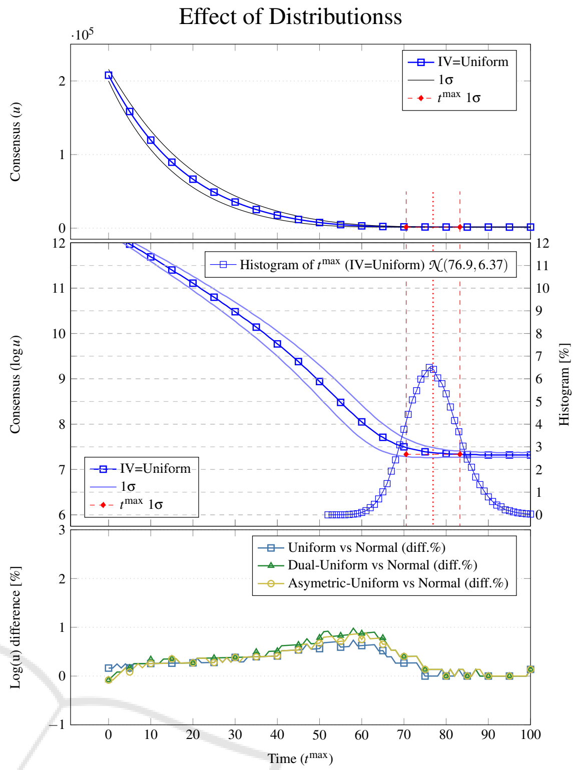

Figure 4: (Top) Various simulations of the 10-group showing the consensus measure over time when the initial distribution of views are Uniform. (Middle) The same data as in top graph, but now using $\log_e$(consensus). Histogram of the time it takes to reach consensus over many such runs ($\mu = 76.9$, $\sigma = 6.37$, n=200000). (Bottom) A difference plot to highlight the impact of initial view on the consensus profile.

standard-deviation of views, rather than the type of distribution, at least for the set of distributions we have used. This was not predicted in the construction of the initial mathematical model published in Vorster and Leenen (2023a) and in future work it would be worth re-visiting that model and simplifying it using the findings from this study.

The simulator is written in Python, and the general architecture is such that a scenario consisting of a set of parameters is registered with the simulation class which manages the execution of scenarios. Many scenarios can be registered in sequence before the simulations start.

The scenario parameters include the number of agents involved, artefacts involved, team structure and communications channels between agents, the number of topics under discussion, the distributions used for initial views of agents, and the agent and topic selection strategies that will be used. Finally, the total number of simulations that will be executed per scenario parameter is specified (n=20000 in this case).

The simulator is multi-threaded, each threat executes a specific scenarios repeatedly for a set time (usually 60 seconds) and once that time is reached the thread terminates after the current scenario has finished execution. Results are appended to various logs. Every few minutes (30 in the default configuration) the logs are processed and statistics are calculated for the results files. The results files are such that they can be directly processed in this LaTeXdocument.

Various progress files are kept up to date so that simulations can be stopped at any time and re-started later without the loss of data and very importantly time.

4 RESULTS

Figure 5 shows the results from the simulations. The top left plot shows that scenario where agent and topic selection is completely random and this scenario also acts as the baseline to compare the other scenarios against. For this scenario it takes on average 498.32 ($\sigma = 59.80$, $n = 400000$) time steps to reach consen-

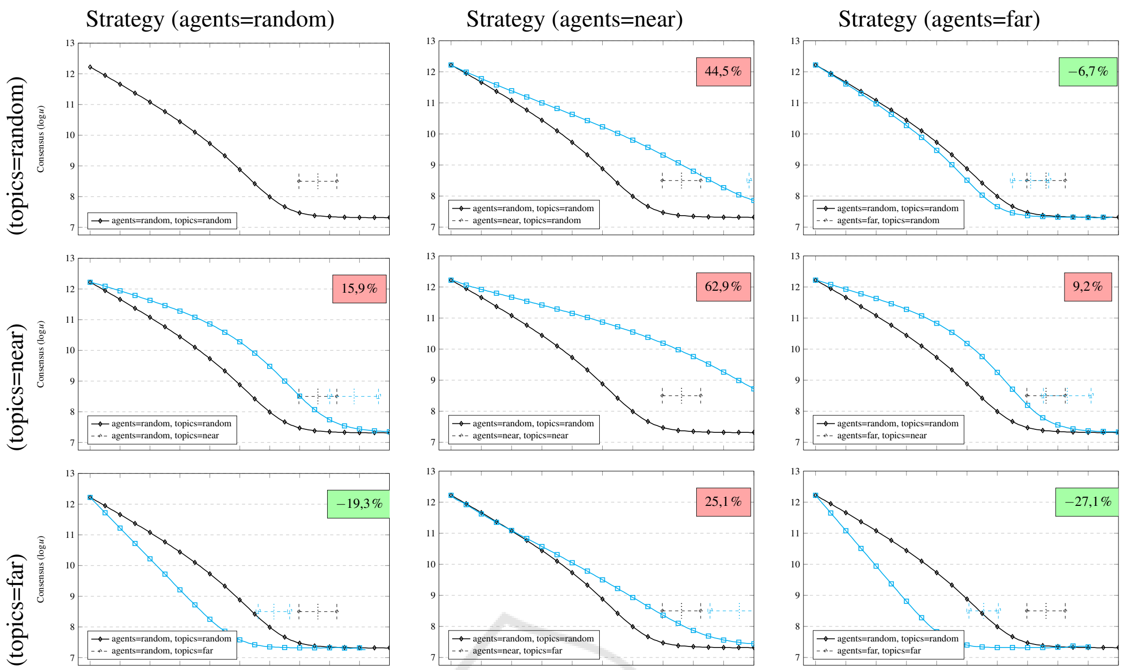

Figure 5: Agent selection strategies are presented on the horizontal axis and topic selection strategies on the vertical axis. The black (diamond) plots are the baseline (random agent selection and random topic selection) against which the other strategies are measured. Each strategy combination also shows the percentage improvement as measured against this baseline. Green (negative percentage) indicate faster time to reach consensus and a red (positive percentage) indicate longer time to reach consensus.

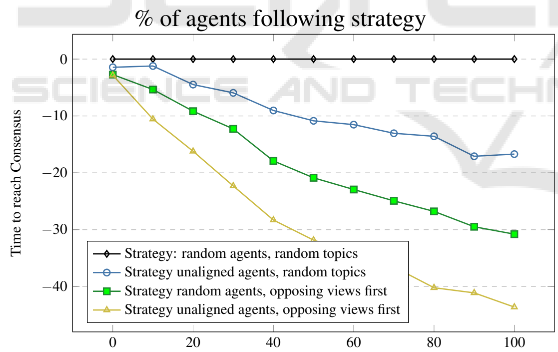

Figure 6: The effect of number of agents in the group on the time to reach consensus relative to the random agents, random topics strategy.

sus. The specific number of time-steps are not relevant, but the relative difference as shown in the graphs are the measure we employ for comparison.

First let us discuss the strategies where agents opt to first align with agents that are already close in terms of their views, Strategy (agents=near), middle column of Figure 5). All these strategies show a significant *increase* in time to reach consensus Strategy (topics=random) +44,5 %, (topics=near) +62,9 %, and (topics=far) +25,1 %.

Similarly, Strategies (topics=near), middle row in figure Figure 5, show increases in time to reach consensus of +15,9 %, +62,9 %, and +9,2 % for (agents=random), (agents=near), and (agents=far) respectively.

The strategies that lead to improvements in time to reach consensus are to prioritize unaligned agent (agents=far), opposing views (topics=far), or both, with 6,7 %, 19,3 %, and 27,1 % improvements respectively.

To understand how these results change with the percentage of agents following the strategy (as opposed to random), we ran a large number of experiments (n=400000 per point) with 100 agents in the group, and varying the number of agents that follow a specific strategy. We report here only on the strategies that improve time to reach consensus.

There results are shown in Figure 6 and from inspection of these graphs, are only approximately linear. It shows that the more agents follow the strategy the bigger the results, as expected.

Finally, we want to further explore the topic selection strategy and in particular if there is a difference in prioritizing members on the same side of an issue first versus the above strategy of far and near classifications. To do this we define four topic-selection strategies based on if the two agents are one the 'same side' of an issue versus on the opposite side and if their views are near or far from each other.

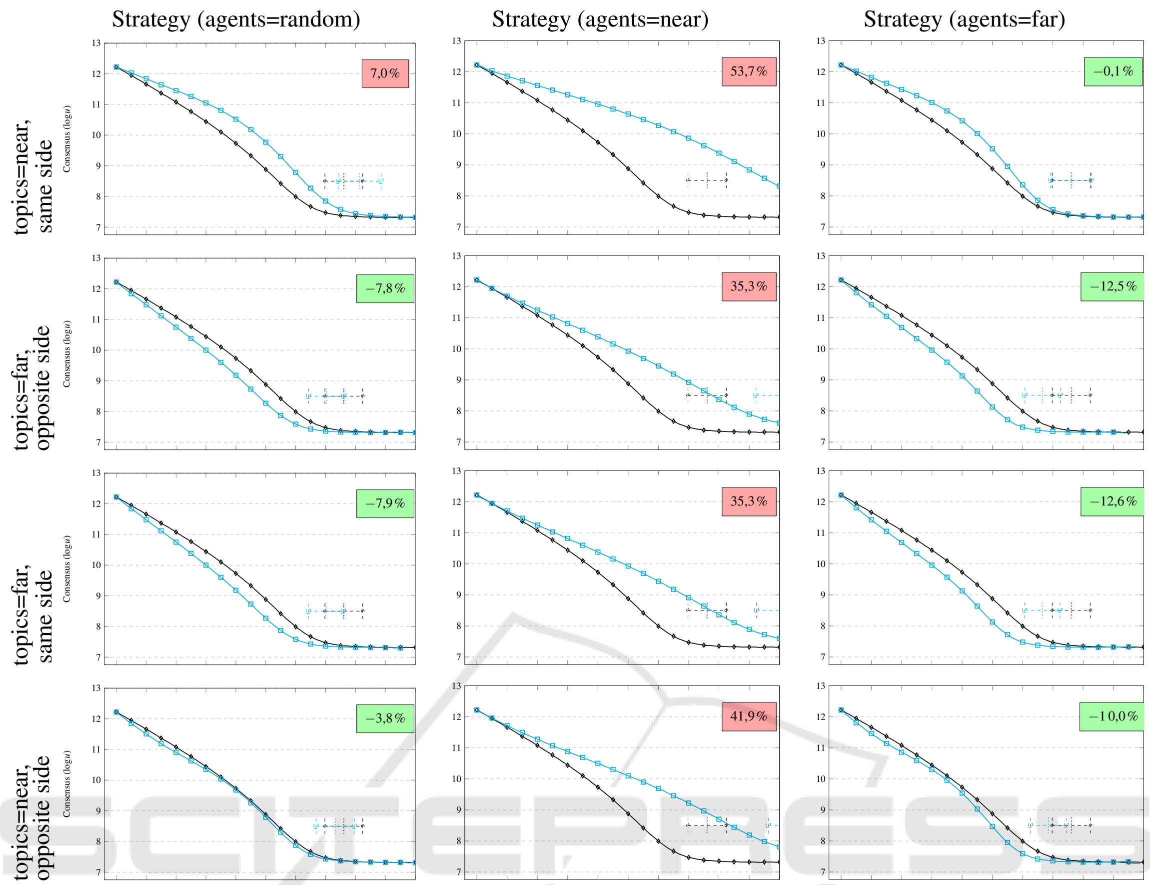

Figure 7: Agent selection strategies are presented on the horizontal axis and topic selection strategies on the vertical axis. The black (diamond) plots are the baseline (random agent selection and random topic selection) against which the other strategies are measured. Each strategy combination also shows the percentage improvement as measured against this baseline. Green (negative percentage) indicate faster time to reach consensus and a red (positive percentage) indicate longer time to reach consensus.

The results are shown in Figure 7 and indicate that (agents=far) Strategies dominate any other agent selection strategy.

However, the interesting part is comparing the results from Figure 7 to that of Figure 5. In particular it seem that broadly prioritizing far agents irrespective of perceptions of 'side' (topics=far, agents=random, −19,3 % in Figure 5) is better than selecting agents based on perceptions of side (topics=far opposite side, −7,8 %, and topics=far same side, −7,9 % in Figure 7).

5 DISCUSSION

5.1 Interpretation of Results

Our findings indicate that strategies prioritizing unaligned agents and opposing views significantly enhance consensus efficiency. Specifically, the strategy of selecting agents with the most divergent views and discussing topics with the greatest differences *first* resulted in the most improvement in time to reach consensus compared to random strategies. This suggests that addressing the most contentious issues early can streamline the consensus process by preventing the entrenchment of opposing views and is a superiour strategy to first building a core of support. Strategies that focused on aligning with agents already close in views or discussing similar topics first led to increased time to reach consensus. This outcome highlights the potential inefficiency of reinforcing existing agreements without addressing underlying conflicts.

It is important to address issues that have a high difference in views early irrespective of perceptions of 'side'. The results clearly show that ignoring far from the norm views within perceived 'same' side team members can still extend the time to reach consensus and a better strategy is to address issues irrespective of perceived membership sides.

5.2 Implications for Organizational Practice

These results have practical implications for project management and organizational decision-making. In environments where rapid consensus is critical, such as in project execution, prioritizing engagement with dissenting opinions and contentious topics can expedite decision-making processes. This approach may also foster a more inclusive environment by ensuring that diverse perspectives are considered and integrated early in the decision-making process.

5.3 The Role of Initial View Distributions

Interestingly, our study found that the initial distribution of agent views (whether normal, uniform, dual-uniform, or asymmetric-uniform) had negligible effects on the time to reach consensus, provided the standard deviation was constant. This suggests that the diversity of initial opinions, rather than their specific distribution, is a more critical factor in consensus dynamics. This finding challenges traditional assumptions and suggests new avenues for simplifying mathematical models of consensus processes.

5.4 Limitations and Future Research

While our study provides valuable insights, it is not without limitations. The simulations were conducted in a controlled environment with specific assumptions about agent behaviour and interaction. Future research could explore more complex models incorporating factors such as dynamic network topologies, varying levels of agent influence, and real-world constraints.

Additionally, the impact of subversive agents on consensus processes warrants further investigation. Understanding how these agents can be managed or mitigated could provide further improvements in consensus efficiency.

6 CONCLUSION AND FUTURE WORK

Earlier research on the causes of project failures, delays, and cost overruns have identified lack of consensus as one of the key contributing factors. The consensus formation process is time-consuming, and often left out of project planning or its effort is underestimated.

In this study, we explored the impact of agent selection and topic prioritization strategies on the efficiency of consensus formation within multi-agent systems. Our findings indicate that strategies prioritizing unaligned agents and contentious topics enhance the speed of reaching consensus. Specifically, engaging with agents holding divergent views and addressing the most contentious issues early in the process can streamline consensus-building by preventing the entrenchment of opposing views. Conversely, strategies focusing on aligning with agents already close in views or discussing similar topics first tend to prolong the consensus process and is a less efficient strategy.

These insights have practical implications for organizational decision-making and project management. By prioritizing engagement with dissenting opinions and contentious topics, organizations can expedite decision-making processes and foster a more inclusive environment that integrates diverse perspectives early on. Furthermore, our study reveals that the initial distribution of agent views, provided the standard deviation remains constant, has negligible effects on the time to reach consensus. This suggests that the diversity of initial opinions is more critical than their specific distribution, challenging traditional assumptions and offering new avenues for simplifying mathematical models of consensus processes.

Despite the valuable insights gained, this study is not without limitations. The simulations were conducted in a controlled environment with specific assumptions about agent behavior and interaction. Future research could explore more complex models incorporating dynamic network topologies, varying levels of agent influence, and real-world constraints. Additionally, the role of subversive agents in consensus processes warrants further investigation. Understanding how these agents can be managed or mitigated could provide further improvements in consensus efficiency.

Future work could also focus on developing adaptive strategies that dynamically adjust agent and topic selection based on real-time feedback from the consensus process. Exploring the integration of machine learning techniques to predict and optimize consensus pathways could offer significant advancements in the field.

REFERENCES

Al-Ahmad, W., Al-Fagih, K., Khanfar, K., Alsamara, K., Abuleil, S., and Abu-Salem, H. (2009). A taxonomy of an it project failure: root causes. *International Management Review*, 5(1):93.

Amirkhani, A. and Barshooi, A. H. (2022). Consensus in multi-agent systems: a review. *Artificial Intelligence Review*, 55(5):3897–3935.

Barabási, A.-L., Albert, R., and Jeong, H. (2000). Scale-free characteristics of random networks: the topology of the world-wide web. *Physica A: statistical mechanics and its applications*, 281(1-4):69–77.

Chang, M.-H. and Harrington, J. E. (2000). Centralization vs. decentralization in a multi-unit organization: A computational model of a retail chain as a multi-agent adaptive system. *Management Science*, 46(11):1427–1440.

Dunbar, R. I. (1998). The social brain hypothesis. *Evolutionary Anthropology: Issues, News, and Reviews: Issues, News, and Reviews*, 6(5):178–190.

Erdős, P., Rényi, A., et al. (1960). On the evolution of random graphs. *Publ. Math. Inst. Hung. Acad. Sci*, 5(1):17–60.

Iacopini, I., Petri, G., Baronchelli, A., and Barrat, A. (2022). Group interactions modulate critical mass dynamics in social convention. *Communications Physics*, 5(1):64.

Keupp, M. M., Palmié, M., and Gassmann, O. (2012). The strategic management of innovation: A systematic review and paths for future research. *International journal of management reviews*, 14(4):367–390.

Kian, M. E., Sun, M., and Bosché, F. (2016). A consistency-checking consensus-building method to assess complexity of energy megaprojects. *Procedia-social and behavioral sciences*, 226:43–50.

Leishman, T. G., Green, D. G., and Driver, S. (2009). Self-organization in simulated social networks. In *Computer-Mediated Social Networking: First International Conference, ICCMSN 2008, Dunedin, New Zealand, June 11-13, 2008, Revised Selected Papers*, pages 150–156. Springer.

Michalski, R., Serwata, D., Nurek, M., Szymanski, B. K., Kazienko, P., and Jia, T. (2022). Temporal network epistemology: On reaching consensus in a real-world setting. *Chaos: An Interdisciplinary Journal of Nonlinear Science*, 32(6).

Reagans, R., Miron-Spektor, E., and Argote, L. (2016). Knowledge utilization, coordination, and team performance. *Organization Science*, 27(5):1108–1124.

Sáenz-Royo, C. and Lozano-Rojo, A. (2023). Authoritarianism versus participation in innovation decisions. *Technovation*, 124:102741.

Stocker, R., Green, D. G., and Newth, D. (2001). Consensus and cohesion in simulated social networks. *Journal of Artificial Societies and Social Simulation*, 4(4).

Vorster, J. and Leenen, L. (2023a). Consensus simulator for organisational structures. In *Proceedings of the 13th International Conference on Simulation and Modeling Methodologies, Technologies and Applications*, pages 15–26.

Vorster, J. and Leenen, L. (2023b). Exploring the effects of subversive agents on consensus-seeking processes using a multi-agent simulator. In *Proceedings of the 13th International Conference on Simulation and Modeling Methodologies, Technologies and Applications*, pages 104–114.

Vorster, J. and Leenen, L. (2024a). The unreasonable effectiveness of artefacts and documentation: An exploration of consensus using multi-agent simulations in a two-team configuration. In *Proceedings of the 14th International Conference on Simulation and Modeling Methodologies, Technologies and Applications – SIMULTECH*, pages 313–323.

Vorster, J. S. and Leenen, L. (2024b). Exploring the impact of subversive agents on consensus processes in project teams: Multi-agent simulations. In Wagner, G., Werner, F., and De Rango, F., editors, *Simulation and Modeling Methodologies, Technologies and Applications*, pages 29–60, Cham. Springer Nature Switzerland.

Vorster, J. S. and Leenen, L. (2024c). Stochastic consensus simulation fororganizational cooperation. In Wagner, G., Werner, F., and De Rango, F., editors, *Simulation and Modeling Methodologies, Technologies and Applications*, pages 139–173, Cham. Springer Nature Switzerland.

Waheeb, R. A. and Andersen, B. S. (2022). Causes of problems in post-disaster emergency re-construction projectsiraq as a case study. *Public Works Management & Policy*, 27(1):61–97.

Watts, D. J. and Strogatz, S. H. (1998). Collective dynamics of small-world networks. *Nature*.

Whitney, K. M. and Daniels, C. B. (2013). The root cause of failure in complex it projects: Complexity itself. *Procedia Computer Science*, 20:325–330.

Will, M. G., Al-Kfairy, M., and Mellor, R. B. (2019). How organizational structure transforms risky innovations into performance–a computer simulation. *Simulation Modelling Practice and Theory*, 94:264–285.

Xie, J., Sreenivasan, S., Korniss, G., Zhang, W., Lim, C., and Szymanski, B. K. (2011). Social consensus through the influence of committed minorities. *Physical Review E*, 84(1):011130.

Yan, H.-B., Ma, T., and Huynh, V.-N. (2017). On qualitative multi-attribute group decision making and its consensus measure: A probability based perspective. *Omega*, 70:94–117.