Bee-Inspired Evaluation Algorithm Leads to Improved Decision Making in Groups

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Abstract—The emergence of technology as a fundamental centerpiece in everyday life has allowed for more connections and human groups than ever before. Each of these groups faces decisions that impact all members, ranging from the type of food to order for an event to relocating a company’s headquarters. Traditionally, groups might make a decision by asking members to vote or by having a committee make an executive decision. However, these traditional means do not handle situations with many possible solutions well, nor leverage the experience of the group members. Humans are not the only, nor even the first creatures to make group decisions. We can look to social insects which make decisions for colonies of up to tens of thousands of individuals. Drawing inspiration from how honey bees, *Apis mellifera*, find new nest sites, the bee-inspired evaluation (BIE) algorithm was developed. This mechanism was modeled and shown that simulated groups make decisions that average within 0.2% of the optimal choice. Simulated groups consistently made less error-prone decisions using the BIE algorithm when compared to a simple majority voting system.

Index Terms—Bioinspiration, decision-making mechanism, group decision making, honey bees.

I. INTRODUCTION

AlTHOUGH individuals are capable of making good decisions, their propensity for nonrationality has been well documented [1]. In principal, a successful group decision should maximize the social welfare of the entire group. However, the social welfare maximization might not be aligned with each individual maximizing their individual value, or utility function [2]. We can learn from other social groups (ants, dolphins, primates, etc.) and apply lessons learned from nature to improve human decisions made in organizations.

The honey bee (*Apis mellifera*) provides a distinct alternative to human decision making in social groups. During honey bee swarming, a group of bees, as shown in Fig. 1, will make decisions in the best interest of the colony, (for a comprehensive overview of the research done on decision making in honey bees see [3]). A subgroup of bees, the scouts, will evaluate and choose potential new nest sites. In the process, an individual bee evaluates a subset of the total number of potential choices and makes a judgment independently. Once some number of individuals have all reached the same decision, the decision is made for the group. In this paper, we propose the bee-inspired evaluation (BIE) algorithm, a process human groups can use to make more robust decisions in large decision spaces. This paper covers a brief background of current methods human groups use in making decisions, the challenges in making decisions in large decision spaces, how hives of honey bees can be used as an alternative method, the method behind modeling the proposed algorithm, results of how the algorithm performed in simulation, a discussion on the implications and limitations, and a mock situation the algorithm could be used for.

II. CURRENT METHODS FOR DECISION MAKING IN LARGE GROUPS

There are three commonly used methods for decision-making in large groups which are considered in this paper: Consensus, unilateral, and simple-majority democracy. This is not a comprehensive list of methods, but it includes the mechanisms used most often for decision making among many individuals. What follows is a brief description of each method.

A. Consensus

A consensus-based decision is when a group decides to make a decision only when all, or nearly all, members of the group agree. Trial jury decisions are an example of this method. Another version of this is the Quaker-based model, which follows a precise structure used to facilitate discussion and consensus. A disadvantage of the consensus model is the difficulty of getting a diverse group of individuals, who might have varying utility functions (rank alternatives differently because the options differ in value to the individuals), to agree or agree in a timely
manner. Additionally, this method does not lend itself to groups which have a large number of members.

B. Unilateral

A unilateral decision is when a single individual or a very small proportion of the group makes the decision for the whole group. A dictator makes unilateral decisions for their country. This form of decision making is also common in corporations where a CEO and the executive team have the power to make decisions which impact the whole organization without consulting large portions of the group. Although this method can be decisive, it has many limitations. For one, knowledge and perspective are only provided by selected individuals, who likely have a similar backgrounds and experiences.

C. Simple Majority Voting

There are many forms of democracy, whether they are representative or direct, but we will consider a simple majority democracy where every individual votes for their first-choice preference. The option which receives the highest number of votes is the group’s decision. To reach a majority, a run-off election might have to occur first. An advantage of simple majority voting is that everyone in the group can participate. A main disadvantage is that individuals are not always good at making rational decisions and the majority does not always pick the option which optimizes social welfare.

III. CHALLENGES IN GROUP DECISION MAKING IN LARGE DECISION SPACES

As previously mentioned, humans tend to make mistakes when making decisions, especially when given many options, or when making decisions as a group. Although there are several items that can cause an individual to act nonrationally, two pertinent phenomena, information overload and the price of anarchy are discussed later. These phenomena are relevant because they have direct implication on the performance of the BIE algorithm. The analysis into the impact of a large decision space is seen in Section IV-B. Differing utility functions, which can influence the price of anarchy, are accounted for when modeling in the perception error (PE) (see Section V-B).

A. Information Overload

A phenomenon that can impact a decision-making process and the quality of the decision is information overload, defined in this paper as “a state of affairs where an individual’s efficiency in using information in their work is hampered by the amount of relevant and, potentially useful, information available” [4]. The number of potential outcomes and the number of factors that need to be considered can increase the decision space and thus the amount of relevant information an individual must consider. When presented with a sufficiently large decision space, individuals can experience information overload which results in stress, slow decision making, lower decision satisfaction, and poor decision making [4], [5]. The BIE algorithm presented later can handle situations with large decision spaces because it instructs individuals to only evaluate a small subset of the decision space instead of the entire realm of possibilities.

B. Price of Anarchy

Price of anarchy is a metric commonly used in game theory. It describes the ratio between the outcomes at a situation’s equilibria to the optimal outcome of the situation [2]. An equilibrium is an outcome of a situation in which if any individual changed their actions it would only result in an equal or worse outcome for that individual. In some scenarios, this selfish behavior can result in a price of anarchy as low as 0, meaning social outcome when all players act selfishly is nonexistent (this is for situations where a higher outcome denotes a benefit)

\[
\text{Price of Anarchy} = \frac{\text{outcome at equilibria}}{\text{optimal outcome}}. \tag{1}
\]

In situations with a poor (low outcome value) price of anarchy, coming up with a group decision that has a beneficial outcome can be difficult. The BIE algorithm, explained below, does not attempt to solve this problem; therefore, this algorithm should only be applied to dilemma in which participants have aligned utility functions and where the price of anarchy is near 1.

IV. HONEY BEE SWARMING AS AN ALTERNATIVE FOR DECISION MAKING IN LARGE GROUPS

Although there is no firm limit on the size of a honey bee colony, wild colonies must deal with the spatial constraints of their hive location. As a colony begins to outgrow its hive, a swarm is produced which includes about two-thirds of the original hive and the mother queen. The swarm will cluster around a branch or similar location near the hive while some of the oldest bees in the swarm, the scout bees, venture out to look for, and decide upon, a new nest site for the colony. This process is referred to as swarming and the decision-making process typically occurs over a few days [3], [6].

When a scout bee finds an acceptable location for the new hive, she returns to the swarm to report and begins her dance. This dance communicates the direction, distance and the scout’s assessment of the potential site. It has been shown that the better a honey bee perceives her site to be, the more vigorously she dances, meaning she performs the dance longer, faster, and with more circuits [7], [8]. Scout bees at the swarm might encounter another bee dancing and then be recruited to investigate the site for themselves. If they also deem the site to be favorable, they will return and dance in support of the same site. Again, with more vigorous dancing denoting more favorable sites. Scout bees are more likely to encounter bees dancing vigorously (since vigorous dancers dance for longer), which recruits more individuals and so-on.

Before the swarm flies to its chosen nest site, usually all the dancing bees are dancing in support of the same site. One might be tempted to think that this is the condition for deciding, however that is incorrect. Honeybees only have a local knowledge; an individual bee knows that the bees around her might be dancing but has no global knowledge. In fact, there have been recorded instances in which a swarm begins to fly to their nest site, however one sub-population tries to fly in one direction and a different sub-population tries to fly to a different nest site.

The decision for a nest location is made by quorum sensing. Once there are a certain number of scout bees actively at a single
potential nest location (approximately 15 individuals in honey bee colonies [4]) the decision is made. This is called reaching a quorum or quorum sensing. It is possible, although unlikely, that a quorum can be reached at two different sites simultaneously.

There are several details that facilitate this swarming process. First, the whole colony does not participate. Only 3%–5% of the colony will participate in scouting and dancing. For a typical swarm size of 10,000 individuals, this equates to 300–500 individuals acting as scouts [3].

Second, not all scouts are active at the same time. Individual scouts might investigate a site, return to dance, continue to investigate the same or other sites, and maybe return to dance again. However, at a certain point she will stop dancing, no matter the quality of the site she was advocating for [3]. If her site is favorable, other bees will continue to visit and dance. If her site is not favorable, the number of individuals advocating it will wane. There are no “stubborn” bees, which is one reason reaching two quorums simultaneously is a rare occurrence.

Third, all honeybees share the same utility function, which is to propagate their genetic material as much as possible. The more favorable the nest site, the likelier the colony will be to survive and prosper. There is no incentive for scouts to misrepresent their evaluations, making this mechanism dominant strategy incentive-compatible [9] and with a price of anarchy of 1. Each bee is incentivized to evaluate nest sites truthfully, as truthful representations will lead to the colony moving to the most favorable location. In this way, each bee’s utility function and social welfare is maximized simultaneously.

V. METHODS

A. Proposed Decision

The BIE algorithm was inspired by the honeybee swarming process detailed above. The process involves multiple rounds, with a small number of individuals participating in each round, e.g., 10. In a round, each individual makes an independent assessment of the choices. If there are many potential choices, individuals should only assess a subset of the choices to avoid information overload. When modeling this algorithm, the authors chose to have each simulated participant randomly assess an average of five options in the first round. In subsequent rounds, simulants considered options chosen from the previous round and as well as an average of five additional options. Reason being that the additional cognitive load of considering already evaluated options would be minimal. Previous literature has suggested six options is an optimal limit [5] to avoid information overload.

At the end of a round, each individual presents their chosen solution to all members of the subsequent round. Once a person selects their chosen solution, they no longer participate. Individuals in the subsequent round can investigate presented solutions or alternative solutions as they see fit.

A decision is reached when one of two conditions is met. First, if all individuals in a round select the same choice then a decision has been made. The second is if, over the multiple rounds, enough individuals all choose the same option. This is akin to the honeybee quorum sensing. There is a clear tradeoff between quorum size and reliable quality of the decision made. There is also a tradeoff between quorum size and total number of individuals participating in the decision-making process. These tradeoffs are looked at in more detail in Section VI. For further clarity, Fig. 2 shows a flowchart of the BIE mechanism.

To evaluate BIE, it was modeled, and multiple analyses were done to investigate how such a mechanism might perform.

B. Process for Modeling and Evaluating Proposed Decision

The model works by populating a choice matrix, where each choice has a randomly generated absolute score (AS) between 0–100, where higher scores denote better choices. During each round, ten simulated participants select the choice they perceive as having the highest score. Participants do not evaluate every potential choice, but a randomly generated subset of choices, averaging five. If, at the end of a round, every simulated participant selects the choice they perceive as having the highest score. Participants do not evaluate every potential choice, but a randomly generated subset of choices, averaging five. If, at the end of a round, every simulated participant selects the same option then the decision is made. Otherwise, preferences are noted and added to the cumulative votes or quorum tally. Once the number of cumulative votes meets or exceeds the quorum, then a decision is made. For example, consider Table I in which there is a quorum of 12 and the decision is made in the second round.

In the computer model, simulated individuals evaluate the choices based on a perceived score (PS) matrix not the ASs. The PS accounts for perceptions errors, variability in individual utility function and has each individual only evaluating a smaller subset of the total choices instead of the entire choice array. The derivation of PS and its variables are detailed as PS matrix—the
perception that each participant \(i\) has of each choice \(j\)

\[
PS(i, j) = (AS(j) + PE(i) \times PM(j)) \times \text{seen}(i, j). \tag{2}
\]

Detection probability (DP)—the probability of which choice \(j\) is “seen” by individual \(i\).

If choice was selected in previous round

\[
DP(j) = 1
\]

Else:

\[
DP(j) = \frac{\text{average number of choices to be evaluated by each individual}}{\text{total number of choices}}. \tag{3}
\]

\[
\text{Seen} - \text{variable which converts DP}(j) \text{ from a probability to a binary input which determines if choice } j \text{ is perceived by individual } i.
\]

If \(\text{seen}(i, j) = 1\) then participant, \(i\), can evaluate choice, \(j\). If \(\text{seen}(i, j) = 0\) then participant, \(i\), cannot evaluate or “see” choice, \(j\).

The logic is as follows where \(\text{rand}\) is a randomly generated number between 0 and 1.

\[
\text{If } DP(j) = 1, \text{ then } \text{seen}(i, j) = 1
\]

\[
\text{else if } \text{rand} \leq DP(j), \text{ then } \text{seen}(i, j) = 1
\]

\[
\text{else if } \text{rand} \geq DP(j), \text{ then } \text{seen}(i, j) = 0
\]

PE—the error by which an individual, \(i\), perceives a choice’s score. This is a modifier that changes how an individual perceives the AS array. For this model, the PE for an individual \((i)\) was calculated as follows, where \(\text{rand1}\) and \(\text{rand2}\) are randomly generated numbers between 0 and 1. The authors chose to have PE scores represent an error of \(\pm 10\%\). This means if a choice had an AS of 30, some individuals could perceive the score as low as 20 while others could perceive it as high as 40

\[
PE(i) = (\text{rand1} - \text{rand2}) \times 10. \tag{5}
\]

This results in PE scores between \(-10\) and \(10\), with each individual having a different score.

There are two ways to interpret this modifier. First, it could be viewed as a stand-in for an individual’s utility function. In honey bees, the decision that is best for the collective colony is the decision that is best for the individual. This is not true in many cases for humans. This PE can be understood as the utility an individual derives from a choice being different than a different individual.

Second, this could also be understood as an individual’s ability to accurately evaluate choices. Different individuals might be more familiar with an issue. Additionally, everyone has certain biases which make them perceive reality different than it really is. Some people are better at objectively evaluating different options. PE can be interpreted as how good an individual is at perceiving reality.

Perception modifier (PM)—how a choice \((j)\) modifies the PE \((i)\) of individuals is based on if the choice has been selected in a previous round. As more individuals choose a certain option, subsequent individuals perceive the choice’s score closer to its AS. The reasoning is that if more individuals are assessing an option, the advantages and disadvantages of the potential solution are better understood by later evaluators. All PM scores start at 1. If a choice is selected in a later round, the PM score decreases more than if the choice is selected in an earlier round

\[
PM(j) = \frac{PM(j)}{\text{round}}. \tag{6}
\]

### Table II

| Quorum Level | Average Rounds (10 people/round) | Average Error (%) |
|--------------|----------------------------------|-------------------|
| 10           | 3.61                             | 0.132             |
| 15           | 4.39                             | 0.066             |
| 20           | 5.18                             | 0.028             |
| 25           | 6.93                             | 0.033             |
| 30           | 6.63                             | 0.005             |
| 35           | 7.58                             | 9.76 x 10^-4      |

Fig. 3. Percent error versus quorum size.

Error is calculated as the percent error between the AS of the optimal solution and the decision selected for a single iteration. Average error, which was reported in the tables in Section VI, is the average error across all iterations of given condition, where “\(n\)” is the total number of iterations at said condition

\[
\text{Error} = \left(\frac{|AS(\text{optimal solution}) - AS(\text{chosen solution})|}{AS(\text{optimal solution})}\right) \times 100
\]

\[
\text{Average Error} = \frac{\sum_{n=1}^{n} \text{Error}(n)}{n}. \tag{8}
\]

### VI. Results

#### A. Quorum Size

Selecting a quorum size is an important factor in implementing BIE. For this paper, quorum size was set at multiple levels, with the model performing 100 iterations at each increment with each iteration generating a unique set of randomly generated choices and simulated participants. Results were measured in terms of error and rounds required to make a decision. Error was measured as the percent error difference between the AS of the chosen option and the maximum AS of all options.

Results can be seen in Table II. This study was performed with a decision space of 100 options. As predicted, a larger quorum size will result in a lower error on average, as shown in Fig. 3, but will take more rounds to reach a decision. A higher quorum...
can also result in more variability in the number of rounds taken, this can be seen in Fig. 4.

B. Size of Decision Space

It was of interest to explore how BIE performs depending on how large of a decision space it encounters. If there are a small number of potential outcomes, or choices, does that result in less error than if there are many potential outcomes?

To study this, the number of potential choices was varied from 25 to 200 by increments of 25, resulting in 8 conditions. Quorum size was held constant at 15 and the algorithm was performed 100 times for each condition. This simulation was then performed four times (runs 1–4). As might be expected, with more choices, the average number of rounds to reach the quorum increases. However, there is no obvious correlation between the number of total choices and the error in the outcome. This means if there is a large decision space, it might take longer, or more individuals, to reach a decision, but the quality of a decision is not significantly impacted (see Table III; and Figs. 5 and 6). It is important to note here that both the magnitude of error at each condition, measured in percent, and variations in error between conditions and runs is low.

C. Comparison Between BIE and Simple Majority Voting

The BIE algorithm was also compared to a simple majority voting democracy. For this comparison, there were 100 choices.

### Table III

| Number of Choices | Average Rounds (10 people/round) | Average Error (%) (Run 1) | Average Error (%) (Run 2) | Average Error (%) (Run 3) | Average Error (%) (Run 4) |
|-------------------|----------------------------------|---------------------------|---------------------------|---------------------------|---------------------------|
| 25                | 3.03                             | 0.126                     | 0.016                     | 0.066                     | 0.133                     |
| 50                | 3.73                             | 0.081                     | 0.048                     | 0.105                     | 0.089                     |
| 75                | 4.16                             | 0.054                     | 0.053                     | 0.101                     | 0.110                     |
| 100               | 4.68                             | 0.037                     | 0.057                     | 0.063                     | 0.049                     |
| 125               | 4.95                             | 0.021                     | 0.034                     | 0.082                     | 0.054                     |
| 150               | 4.98                             | 0.048                     | 0.050                     | 0.054                     | 0.047                     |
| 175               | 5.09                             | 0.013                     | 0.056                     | 0.012                     | 0.045                     |
| 200               | 5.43                             | 0.28                      | 0.023                     | 0.046                     | 0.043                     |

### Table IV

|                     | Average Percent Error | Maximum Error, Percent | Standard Deviation |
|---------------------|-----------------------|------------------------|--------------------|
| Bee Inspired Evaluation | 0.0617                | 3.937                  | 0.3114             |
| Simple Majority     | 1.796                 | 28.469                 | 2.924              |

The BIE algorithm used a quorum size of 15. From the quorum study in (see Section IV-A), the average number of rounds for a solution with that quorum size is 4.39, if one rounds up to 5 that would be 50 individuals. The simple majority voting had a population of 50 individuals to compare. The simulants in the simple majority cases also made selections based on the PS matrix methodology detailed earlier. A total of 1000 iterations of this was performed, with each iteration being a new set of randomly generated simulated participants and choices.

Although the average error is low for both cases—the voting case has the potential for large variations, whereas BIE does not (see Table IV and Fig. 7).

The error in the BIE algorithm can be decreased by adjusting the quorum size. Theoretically this can also be done with a democratic system. However, to achieve comparable magnitude of error as BIE, the democracy, as modelled, must use at least double the number of individuals.
TABLE V
EXPECTED ALGORITHM PERFORMANCE IN VARIED SITUATIONS

| Expected to Perform | Expected to Perform | Expected Performance Unknown |
|---------------------|---------------------|-----------------------------|
| Well                | Poorly              |                              |
| • Large group size  | • Small Group size  | • Medium Sized              |
| (>100)              | (<40)               | Groups (40 - 100)            |
| • Participants have | • Participants      | • Participants agree on a    |
| aligned utility     | disagree on what a  | goal, but have variation in  |
| functions           | “good” outcome      | utility functions            |
| • Large Decision    | • Small Decision    | • Medium Decision            |
| Space (>10 options) | Space (<4 options)  | Space (4-10 options)        |
| • Diverse group     | • Decision must be  | • Unknown how to             |
| • A close-to-optimal| optimal             | guarantee a decision         |
| decision is         |                     | is within a tolerance of    |
| acceptable          |                     | the optimal solution        |

VII. DISCUSSION

A. Implications

As can be seen from the results, the BIE algorithm has some unique properties and implications (Table V). One clear advantage of using BIE is that a comparatively small number of people with variable backgrounds can evaluate many potential choices without any individual becoming overwhelmed. The model showed, across thousands of iterations, that groups make decisions that are optimal or near-optimal (within 5%) whereas the computer model had a clear optimal choice, the real world is less straightforward.

BIE allows for error, meaning the decision a group comes to might not be optimal. However, it is possible to “tune” this process to an acceptable level by adjusting the quorum size (see Section VI-A). This allows for a user to customize their approach and balance between an acceptable level of potential error and the number of individuals involved in the decision-making process.

During BIE, individuals make independent evaluations. However, at the end of each round, the individuals present their selection to the subsequent round. Any of their research is also available to future participants. In this way, knowledge is shared while avoiding some common pitfalls of normal group decision making like individuals who dominate conversation and group-think. Because the individuals evaluating the choices change each round, this method also avoids the issue of stubborn individuals who can sometimes hamper group decision making, especially in consensus situations.

However, there are some downsides of this information transfer method. Constructive debates can be fruitful in bringing up hidden facets which, without discussion, would not become apparent. When implementing BIE, careful thought would have to be put into the nature of the handoff presentation between rounds to mitigate this concern. Perhaps some sort of discussion or question and answer section could facilitate this.

Another advantage of the BIE mechanism is the ability to draw upon the diversity in background of the group. This process does not require all individuals to be experts, be in the same group or even be in the same geographical location. Although not every individual in a group is polled, BIE draws upon the expertise of individuals across an organization to evaluate a variety of facets of an issue.

BIE might not be the best mechanism for making straightforward decisions such as “yes” or “no” decisions. BIE is also not appropriate for decisions in which individuals in the group might have drastically differing utility functions. For example, in political elections not all voters prioritize the same issues. One individual might own a house and a small business and would get high utility from a candidate who has a certain stance in these areas, while another voter might have children in school and prioritize education issues.

Finally, this process is not feasible if the group making the decision has too small of a population. A committee tasked with making a decision on behalf of a company could call upon other employees as a resource. It can be seen from Section IV-A, with a quorum of 10, it takes on average, 40 people. If the total group population is near or less than 40, BIE could not be reliably applied in the manner described in this paper.

The computer model to simulate BIE uses assumptions. For example, it assumes rational behavior from simulated participants (i.e., an individual always selects the choice they perceive as being “best”) and that utility functions of individuals are reasonably aligned (see Section IV-B). The model also assumes that information transfer between rounds always occurs efficiently (see Section V-B) on PM.

The major limitation of this paper is that the algorithm was only modeled and was not demonstrated with in an experimental setting or in situ. As such, there might be potential unforeseen real-life human factor or implementation issues, such as communicating results between rounds.

B. Implementation and Potential Applications

For a sufficiently large population, the applications for BIE are endless. This process could be achieved with participants in the same location or virtually. It is feasible, and even reasonable, to use the internet and other technologies to facilitate such a process.
For a hypothetical situation in which the BIE algorithm could be used in and how it might be implemented, see Appendix A where a hypothetical situation is presented and BIE is used to solve it. The appendix goes step-by-step through the mechanism as mock employees decide on a new location for a branch opening.

This paper discusses this algorithm in context of groups of humans solving problems, it has other potential application. Although computers are capable of processing huge amounts of data, many problems still have such large solution spaces that it is impractical or impossible to evaluate all permutations. For certain problems in this space, algorithms do exist which can provide optimal or near-optimal solutions. However, depending on the base problem, these algorithms can be difficult to implement, are time consuming and might not yield desired results [10].

The algorithm defined in this paper could provide an alternate strategy. Instead of individuals evaluating a subset of the potential choices, it would be computers evaluating a small fraction of the solution space. At the end of its calculations, each computer would report the best solution found. The computers in the subsequent round would be provided that information and then evaluate a new fraction of the solution space. Once a quorum of computers has reported the same, within a tolerance solution then the decision would be made. It is unknown how the algorithm would perform in this application, but that could be the subject of future exploration.

C. Future Work

This paper focuses on situations in which every individual has an aligned utility function with a PE of ±10%. Future work needs to be done to explore how the BIE algorithm performs when utility functions are less aligned. It would be important to study how this impacts the number of rounds required to make a decision and quality of decision made. Further work might also include a human factors study into potential pitfalls in communication and information transfer between rounds.

VIII. Conclusion

Although humans have been forming groups and making group-based decisions for thousands of years, there exists limited methods to make these decisions. These methods are not the best in certain situations, for example when there are many possible choices. In this regard, there is an example in nature which can be readily drawn in from the honey bee, *Apis mellifera*. Honey bee colonies perform an act called swarming in which part of the colony departs and engages in the decision-making process of finding a new nest location. Not only are honeybees capable of evaluating multiple criteria when assessing whether a site would be a good choice, but colonies are reliably capable of making good decisions even with many possible choices. Using this process, a decision-making algorithm for humans was developed called BIE algorithm. BIE was modeled and shows that with a solution space of 100 different choices, a quorum size of ten would result, in an average of less than 40 people are needed to make a decision and, over 100 iterations, the average percent discrepancy between the optimal solution and the solution selected was 0.132%. BIE was compared to a simple-majority voting system and, over 1000 cases, produced more favorable results for similar population sizes.

APPENDIX A

PRACTICAL EXAMPLE OF THE BIE ALGORITHM

This section details a hypothetical scenario detailing a problem the BIE algorithm could be used for and how it might be implemented.

A. Problem

Company XYZ is a large company and has been experiencing major growth in recent years. As such, they want to expand and open a new, major branch office somewhere in the United States. Instead of having an executive team make a unilateral decision, the company decides to use BIE, which can employ employees across the hierarchy and with different backgrounds, to make this decision.

B. Applicability of the BIE Algorithm

This hypothetical company is large enough that it can feasibly use BIE. Additionally, since all participants are employees, they should have aligned interests. If the new branch does well, the company will prosper and be able to employ more people, give promotions, raises, etc. If the branch does poorly, that might impact the company’s ability to employ and provide benefits to employees. As such, it is in the best interests of all employees to make honest and educated decisions. The BIE algorithm should work well in this situation.

Using BIE is a good way for the company to get perspectives from different areas of the business and explore multiple facets of the issue which an executive team would not be able to do on its own.

C. Setting up the BIE

The group administering the BIE have chosen a quorum of 15, but do not share this information with the round participants. It is important that research and conclusions are available to subsequent participants, but that information should be anonymous to avoid social influences. At any point in time, participants should not know how many cumulative votes one choice has to avoid biasing decisions.

D. Round One

A total of ten initial participants are selected from diverse areas in the company. The group administering the BIE thinks that Chicago, IL, USA, and San Antonio, TX, USA, might good choices and ask participants to consider those two locations as well as 3 or 4 others. Individuals are then asked to return with their recommendation the next morning.

The next morning, round one members present their choices to the ten individuals participating in round two. A presentation might be as simple as, “I considered the following locations and came to the conclusion X was the best choice from that group. This is because it would be close to our current customers and there’s a strong market opportunity for our company in the area.”

Results from round one are given in Table VI.
TABLE VI
EXAMPLE ROUND ONE RESULTS FOR BIE

| Locations       | Round One Votes | Cumulative Votes |
|-----------------|-----------------|------------------|
| Chicago, IL     | 3               | 3                |
| San Antonio, TX | 1               | 1                |
| St. Paul, MN    | 1               | 1                |
| Portland, OR    | 1               | 1                |
| Indianapolis, IN| 1               | 1                |
| Philadelphia, PA| 1               | 1                |

TABLE VII
EXAMPLE ROUND TWO RESULTS FOR BIE

| Locations       | Round Two Votes | Cumulative Votes |
|-----------------|-----------------|------------------|
| Chicago, IL     | 1               | 4                |
| St. Paul, MN    | 3               | 4                |
| Philadelphia, PA| 2               | 3                |
| Portland, OR    | 1               | 2                |
| Seattle, WA     | 1               | 1                |
| Baltimore, MD   | 1               | 1                |
| Indianapolis, IN| 0               | 1                |
| San Antonio, TX | 0               | 1                |

TABLE VIII
EXAMPLE ROUND THREE RESULTS FOR BIE

| Locations       | Round Three Votes | Cumulative Votes |
|-----------------|-------------------|------------------|
| St. Paul, MN    | 5                 | 9                |
| Philadelphia, PA| 2                 | 5                |
| Chicago, IL     | 0                 | 4                |
| Seattle, WA     | 2                 | 3                |
| Baltimore, MD   | 1                 | 2                |
| Tampa Bay, FL   | 0                 | 2                |
| Portland, OR    | 0                 | 2                |
| Indianapolis, IN| 0                 | 1                |
| Palo Alto, CA   | 0                 | 1                |
| San Antonio, TX | 0                 | 1                |

E. Round Two

After the debriefing, round two begins, with participants having access to the details of each previous individual’s research. They also have the flexibility to investigate other options but are encouraged to only evaluate around five total options.

Results from round two are given in Table VII. Round two debriefs their selections to round three.

F. Round Three

After round three, results are given in Table VIII. Round three debriefs their selections to round four.

G. Results

This would continue until one of the locations reached 15 cumulative votes, in which case the quorum would be reached, and the decision made.

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