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Abstract

We propose a hybrid Trustworthy Human-Machine collective decision-making framework to manage Food-Energy-Water (FEW) resources. Decisions for managing such resources impact not only the environment but also influence the economic productivity of FEW sectors and the well-being of society. Therefore, while algorithms can be used to develop optimal solutions under various criteria, it is essential to explain such solutions to the community. More importantly, the community should accept such solutions to be able realistically to apply them. In our collaborative computational framework for decision support, machines and humans interact to converge on the best solutions accepted by the community. In this framework, trust among human actors during decision making is measured and managed using a novel trust management framework. Furthermore, such trust is used to encourage human actors, depending on their trust sensitivity, to choose among the solutions generated by algorithms that satisfy the community’s preferred trade-offs among various objectives. In this paper, we show different scenarios of decision making with continuous and discrete solutions. Then, we propose a game-theory approach where actors maximize
their payoff regarding their share and trust weighted by their trust sensitivity. We run simulations for decision-making scenarios with actors having different distributions of trust sensitivities. Results showed that when actors have high trust sensitivity, a consensus is reached 52% faster than scenarios with low trust sensitivity. The utilization of ratings of ratings increased the solution trustworthiness by 50%. Also, the same level of solution trustworthiness is reached 2.7 times faster when ratings of ratings included.

**Keywords:** Trustworthy Human-Machine Systems, Decision Support Systems, Food-Energy-Water Management, Trust Management, Game Theory

1. Introduction

Decision making is one of the substantially significant problems that people deal with. The primary importance of this field arises from both the complicated nature of the issues and the critical consequences of the decisions. Although making a decision alone could be challenging in some situations, it becomes more troublesome when the decision directly influences more than one party. People have used computers and algorithms to assist in decision making. However, while algorithms can be used to develop optimal solutions under various criteria, it is essential to explain such solutions to the community. More importantly, the community should accept such solutions to be able realistically to apply them. There can be a solution that is supported by every participant; however, it could require a significant amount of effort to reach. To solve these problems, we developed a hybrid Trustworthy Human-Machine collective decision-making framework to assist in the management of Food-Energy-Water (FEW) resources in local rural communities. Our work continues the efforts [1, 2, 3, 4, 5, 6, 7, 8, 9] to make algorithms and Artificial Intelligence more explainable, trustworthy, and applicable by providing a framework for human-machine collaboration specifically for FEW sectors.

Another critical challenge of decision making arises from the essential consequences of the decisions. In this study, we focus on the management of FEW
resources in rural communities that require planning of complex and interdepen-
dent decisions that impact the environment as well as the economic productivity
of sectors and local communities. Besides the magnitude of the consequences, it
also involves multiple stakeholders (also called FEW actors), from farmers to
agencies, which complicate the decision-making process even further. As indi-
cated in the report of the United States Department of Agriculture (USDA) [10],
although today’s agriculture requires farmers to give decisions for the survival
of their businesses, long term effects of the decisions need to be considered for
the sustainability of agriculture in the country. It is also underlined that the
financial incentives, technical assistance, and education may encourage farmers
to take actions to preserve soil.

The application represents the complexity in co-management of natural sys-
tems (e.g., watersheds) and human systems (e.g., agriculture economy) in pres-
ence of large number of stakeholders that must coordinate for overall system
sustainability. Further, many of these decisions are geographic, may vary with
time, and represent multiple types of water, energy, and land management deci-
sions that require sustained coordination between decision makers on the ground
and policy makers. In [11], the difficulties in computation, visualization, applica-
tion, privacy, and security that are specific to the FEW sectors are briefly
mentioned. Reimer et al. [12] proposed a model to show the interaction between
the job market and economic growth and food, water, and energy. In [13], the
challenges faced in ground water monitoring using classical optimization meth-
ods are addressed by using a human-computer collaborative framework for a
specific genetic algorithm; however, the algorithm is improved using expert feed-
back whereas the landowners still need to understand, trust, and accept such
solutions. As a further improvement, Piemonti et al. [14] showed the significance
of incorporating the farmer preferences and the land tenure within watershed
optimizations; however, it can be beneficial both for the society and the envi-
ronment where the farmer preferences are evaluated and a social influence is
formed for fair solutions.

With the rapid growth and adoption of information and computational tech-
nologies in society, FEW actors have an opportunity to utilize sophisticated computer decision support systems where they can (i) organize the development of management solutions and evaluation of feedback, (ii) highlight the supported solutions, and (iii) demonstrate the consequences of nominated and approved solutions on water, land, and energy resources [15]. In this study, we describe a collective decision-making problem among the actors in FEW sectors of a test basin in Oregon, USA, as part of our results in a large USDA-NSF funded project [15]. In our initial models, the actors in the decision making aimed to split a finite and continuous resource [16]. In this proposed hybrid trustworthy human-machine collective decision-making framework, each actor proposes a solution, which is visible to other participants in the decision-making, and rates each other’s solutions, where ratings constitute a basis for our trust model. Furthermore, actors select solutions as a trade-off between their economic profit and environmental protection [14, 17, 18] that represents the risk in our system. This action of actors is judged by the community based on the actor’s ability to make such trade-offs.

In this study, we first review our extended version of measurement theory-based trust management framework which is first proposed in detail in [19]. As we describe the measurements as the ratings given for the proposed solutions, we also utilize ratings of ratings to measure trust in a more advanced way. More importantly, we introduce the notions of trust pressure and trust sensitivity to emphasize the underlying reasoning of our trust model. Before running the simulations for more complex cases, we present a game-theory approach for basic scenarios where the actors try to maximize their trade-offs between economic gain and environment protection, which represent the risk in our system, judged and led by the trust of the community. We provide a solution for a scenario and then present the results for a more realistic one. Lastly, we present a Trustworthy Decision Support System considering the basic and modern decision-making approaches [20, 21, 22, 23, 24] and integrate our measurement theory-based trust management framework. We run our simulations for several different management scenarios where actors select and propose complete solutions from a so-
olution set. We investigate the impacts of utilizing ratings of ratings and also having actors with varying levels of trust sensitivity. Then, we show that when there is a trust pressure on actors, and they acknowledge trust, consensus can be reached in fewer rounds of negotiation on the computational platform.

In our system, the trust pressure will reflect the community characteristics. Similarly, moral norms depend on a given community and will pressure members of that community to satisfy such norms. If the community cares about the environment, then its trust pressure will lead the actors to trade-offs that favor environmental protection. While several works include humans in the loop with algorithms and Artificial Intelligence [25, 26, 27, 28], the novelty of our work has three main aspects. First, the solutions have to be acceptable by stakeholders that might have competing goals. Second, we aggregate and include the feedback of humans in the system using a trust management system. Third, the trust feedback pressures the actors towards a consensus desirable by the community. Our contribution is important because the stakeholders in the FEW sectors, such as farmers, are private owners, and the only way to apply solutions is volunteering which can be reached through negotiations under the community pressure [29, 30, 10].

As discussed in [19], trust applications are very context and application dependent. Therefore, while we use the same trust framework, this is more of a redesign of the system to fit to the FEW scenarios. In more detail, the contributions in this paper are:

- We developed a new trust modeling that means mapping the metrics of our framework, impression, and confidence to reviews and reviews of reviews of actors to each other regarding their decisions
- We used trust operators for trust inference appropriate for FEW scenarios
- We have integrated the results of our trust system with decision making in FEW scenarios.
- We have introduced two new metrics, trust sensitivity and trust pressure,
in our study. Trust pressure quantifies the community’s pressure, and trust sensitivity quantifies how much an actor is influenced by the trust pressure of the group. We integrated trust sensitivity and trust pressure in the framework.

• Based on the above work, we have developed a game-theoretical tool to explore the relationship between trust sensitivity and the distance from some community-desirable solutions.

• Our main goal is to develop a practical tool to assist actors in FEW scenarios; therefore, we show that better and faster community decisions, in the form of trade-offs between the community and individual goals, can be reached using our trust-based decision support system.

The rest of the paper is organized as follows. In Sect. 2, we present the background and related work in decision making, trust, and social influence. In Sect. 3, we review our extended trust management framework explaining the ratings of ratings, trust pressure and sensitivity, and solution trustworthiness. In Sect. 4, we propose a game-theory approach for resource sharing considering trust sensitivities of actors and show its effect to the consensus. In Sect. 5, we present various scenarios of FEW decision makings having discrete solutions and the results of the simulations regarding the trust sensitivities and the utilization of ratings of ratings. Then, we conclude our paper in Sect. 6.

2. Background and Related Work

In this section, we present the background and related work for (i) decision making and its optimization with feedback, (ii) trust and applications of trust frameworks, and (iii) social influence, social capital, and social trust which are the bases for our trust framework approach.

2.1. Decision Making

Fields such as economics, society, and environment require decisions which have significant impacts on people’s life. Unless we have capable and robust
decision-making mechanisms, the results of immature decisions could be cata-

trophic. Also, as the impact area of the decisions moves from local to global,
it becomes more crucial to have a robust system for decisions. Kambiz [20] un-
derlined that the global financial crisis of 2008 is one of the examples where
decisions affected almost every country in the world. He also added that one of
the reasons for complicated decisions is that the world itself is becoming more
connected and complex, and multiple stakeholders from different fields with dif-
ferent perspectives, maybe even with competing objectives, could be engaged in
decision making.

It was also claimed that most of the important decisions in the modern world
are made by multiple stakeholders because of their complex nature [20]. More-
over, none of the entities may have all of the required information and experience
to make the decision appropriately. If the participants of the decision making
are the experts of a specific field, their goal could become reaching a consensus
by discussing the ideas. The process, consequently, turns into a continual pro-
cess with multiple rounds, including expression, discussion, and alteration of the
ideas. In [21], an approach was proposed for minimization of the modifications
to the expert solutions. Hegselmann et al. [31] proposed an opinion dynamics
modeling where agents propose opinions as real numbers in discrete time inter-
vals. They also provide a certainty metric where agents are affected by others
based on their certainty of their opinions. Furthermore, an innovative design
adapting an algorithm was proposed to utilize the feedback from the experts
for an enhanced optimization [13]. However, the behavior of the actors can be
significantly different when stakeholders have conflicting or competing interests,
as in FEW decision makings, where landowners can be pursuing their economic
profit whereas government agencies go after environmental protection [10].

2.2. Trust and Applications of Trust Frameworks

Kong et al. [32] claimed that the role of trust is central to the complete negoti-
tation process. It is also claimed that trust is integral to value creation, trade-
offs, and overcoming the self-interest barriers that limit the social value [33].
Furthermore, all parties benefit from mutual trust which is considered as an important catalyst for negotiations to become smoother [34]. Likewise the lubrication characteristics of trust, deals and negotiators are kept together by its biding property [35]. Similarly, the utilization of trust contributes to the engagement of integrative behaviors and disengagement of disruptive attitudes which together promote joint gain instead of individual gain [36, 37, 38]. Also, with the increasing importance of trust in negotiation, its dynamics [39] and open system perspective [40] are also examined. These studies show that a decision-making framework based on trust can significantly facilitate the negotiation process of decision makings in FEW sectors.

As a context-dependent concept, trust can be highly influential either directly or indirectly in the decision-making process [41, 42, 43]. Having many stakeholders in the decision making and keeping track of the historical measurements could force the trust measurement process to be computerized [44, 45, 46]. There are several studies [47, 48, 49, 50] and surveys [51, 52, 46] on trust management. In [53], existing and proposed schemes are analyzed for internet transactions to understand the measures of trust. In [19], to measure and forecast trust among parties in a community, a measurement theory-based trust management framework was proposed. Also, as a result of the flexibility of this framework, there are various applications of it such as stock market prediction using Twitter data [54] and trust management in social networks [55], cloud computing [56, 57], internet of things [58, 59], health care [60, 61], emergency communications [62], and fake user [63] and crime detection [64].

Trust is also used in several studies regarding decision making. In [65], trust-based decision-making methods were proposed for transactions over the internet. In [66], trust-based consumer decision-making models were introduced for e-commerce. In [67] and [68], a model for multi-stakeholder decision making for water allocation problems and a generic framework for consensus reaching were proposed. We introduced a decision support system using our trust management framework for actors in the FEW sectors for sharing a natural resource [16]. We also proposed advanced versions of our decision support system which can use
discrete precomputed solutions for actors [69], where we introduce our gametheoretical approach to trust-based decision-making scenarios [70], and scenarios with different solution proposal and evaluation criteria [71]. In this study, we further extend our previous research by formulating the game theory results, improving the framework by adding functionalities such as capability of utilizing ratings of ratings and measuring trust pressure and trust sensitivity.

As the ratings can be integral to trust frameworks, a mechanism to rate the given ratings is not uncommon in scenarios where the confidence on the ratings are diminishing. When the rating mechanism is being questioned, the stakeholders need to revise, improve, or redesign the rating systems. Although a concrete method is not provided, there has been various work on utilizing the rating of ratings. For example Saal et al. [72] stated that there has been inconsistencies in psychometric qualities of data in the form of ratings which required revised topology of rating criteria. Furthermore, it becomes an important issue among investors when rating the commercial governance [73] where the authors question the corporate governance rankings and funds [74] where the authors question the leading rating systems for investors. More importantly, Haire et al. [75] claimed that the ratings of the American Bar Association Standing Committee on Federal Judiciary should be questioned because of the bias on the ratings based on the gender and belonging to a minority group. These studies show the necessity of ratings of ratings when the consistency and the fairness of the current ratings are being questioned. However, in decision makings of FEW sectors, there is a clear and straightforward trade-off between economic profit and environmental protection which can result in direct and apparent biased ratings.

2.3. Social Influence, Capital, and Trust

Regarding the behaviors in a society, according to [76], in Theory of Reasoned Action by Fishbein and Ajzen [77], which is a general-purpose model to anticipate and analyze behavior; beliefs, attitudes, and subjective norms influence behavioral intentions. Moreover, Chow et al. [78] surveyed and con-
firmed that a social network and shared goals helped and encouraged people to share their knowledge in their institutions. They also claimed that shared goals contributed to the observed social pressure of the organization. Similarly, in [79], which studied the role of trust specifically in the agriculture sector, it was claimed that trust is essential for the advancement of an active private sector based on microenterprises when actors cannot bank on legal institutions. As shown in these studies, trust can also play an important role in FEW sectors such as when the landowners and the government agencies understand that there needs to be a balance between the economic profit and environmental protection. However, the dynamics of the systems can be significantly different as the landowners can be at risk of going out of business due to imbalanced solutions resulting that they do not propose or accept solutions that provide less profit than a specific threshold that is necessary for their business.

Cialdini [80] defined the social influence as a change in the attitude, behavior, or beliefs because of a pressure originated externally which can be real or imaginary. Also, social proof, or social validation which is known as the informational social influence, is defined as a psychological concept where the people take the actions of others as a reference point and decide on the suitable attitude [81]. Studies [82, 83] showed the effect of social validation where the subjects try to comply with the norms of the community. For example, in [82], the university students tend to volunteer more when they see that other students are volunteering. Another study examining social influence was on the energy conservation of residents of California [84]. The results showed that the most effective factor on energy conservation was normative social influence where the actors are willing to gain the approval of the community. The residents who received the normative messages indicating how much the neighbors are conserving were the ones with the highest energy conservation. Although these studies show the result of the social influence on the people’s behavior, our research is distinctive in several ways. While the energy conservation would benefit both the society and the residents, actors in FEW sectors need to make a trade-off between their economic profit and the environmental protection which creates
a conflict of interest among the actors. Furthermore, the normative messages that the residents receive are anonymous and not directly criticizing the current choice whereas the rating mechanism in our scenarios is a direct feedback on the solutions and the ratings, if applicable.

Pelling and High [85] discussed the contribution of social capital to the actions taken against climate change and cited Putnam [86], where he defined social capital as aspects of social life such as networks, norms, and trust which allow stakeholders to take action together more effectively for common objectives. Jones et al. [87] stressed that enhanced environmental management could be achieved through higher levels of social capital. In many studies [88, 89, 90, 91, 92, 93], the significance of imposing social capital among people to enhance their attitude towards national resource management is expressed. Similarly, Pretty and Ward [94] stated that the fundamental belief for social trust level and its impacts are that people tend to take action towards a shared interest, believing that others in the community will behave similarly. Therefore, the trust level affects the number and density of free-riding behavior [95], which is considered as a notable handicap against natural resource management [96]. Sønderskov [97] also claimed that social trust facilitates settlement on collective action problems through higher participation levels from people in environmental groups. Likewise, Pretty [98] claimed that trust level helps to reduce the transaction costs and to maximize the collaboration among participants. In [99], four types of trust, namely dispositional, rational, affinitive, and procedural trust, and their relevancy regarding collaborative natural resource management are investigated. Consequently, these studies show that the social capital and trust can facilitate the decision making process when the actors acknowledge trust; however, it is difficult to model a system where there is a serious trade-off involving their trust such as a decision of a landowner.
3. Trust Framework

In [19], we proposed a trust management framework to measure the trust between entities in a network with trust anticipation using inference rules and compared it to other frameworks in the extensive survey in [46]. Moreover, we showed its successful adaption to Twitter and Epinions data sets in [54]. For this study, we redesigned the trust modeling for decision makings in FEW sectors by analyzing the interactions between the actors. In [19] and [54], we showed that the capability of adapting different inference formulations results in improved analysis of the system by reducing the error rate. In [19], there are several proposed inference formulations for trust. In this paper, we used the one in which the measurements are averaged for aggregation.

When we investigate such decision makings, actors can propose solutions and rate each other’s solutions. Since the ratings are the expressions of the impression from the rater to ratee, they can be considered as measurements of the trust between them. If the ratings are high, the impression, denoted by $m$, is expected to be high. If the ratings are also consistent, the confidence of the impression, denoted by $c$, is also high. In our scenarios, all ratings are considered to be in $[0, 1]$ where 0 is the lowest, and 1 is the highest possible rating.

Furthermore, as we extend the framework proposed in [19], it required the trust modeling to be designed specifically for FEW decision makings. For example, impression and confidence calculation methods are redesigned for the scenarios where we included ratings of ratings. More importantly, we added the functionality for trust pressure and trust sensitivity to model actors’ behavior more realistically. Finally, similar to the power of a user defined in [54], we added the capability of measuring solution trustworthiness to the framework.

3.1. Ratings of Ratings

In this study, we consider both the ratings and the ratings of ratings as the measurements for the trust between a pair of participants because we believe
that people can adapt their behavior based on the trust feedback of the community. Since there are two different actions defined in our scenarios, namely proposing and rating solutions, actors tend to update their behavior for these actions based on how sensitive they are to the trust feedback that they receive from other participants. In Fig. 1, all three actors propose a solution from the solution set, and we show the ratings of actor 1 given to other actors' solutions. Then, actors 2 and 3 rate actor 1’s ratings, which are not given to their solutions.

In Eq. 1, the impression from A to B, \( m^{A:B} \), is calculated by taking the average of both ratings of A to the proposed solutions of B, \( r^{A:B}_i \), and the ratings of A to the ratings of B to participants other than A and B, \( r^{A,r:B,X}_i \). Since the ratings are in \([0, 1]\), the impressions, as the average of ratings, are also in the same interval.

\[
m^{A:B} = \frac{\sum_i r^{A:B}_i + \sum_k r^{A,r:B,X}_i}{N + M} \text{ where } A \neq B \neq X \tag{1}
\]

As explained in [19] and [54], we inversely relate the confidence to the standard error of the mean. To calculate the confidence, \( c \), we consider all the measurements that we used when calculating the impression, \( m \), as shown in Eq. 2.
3.2. Trust Pressure and Trust Sensitivity

Social psychology, as a subfield of psychology, studies the influence of the imaginary or actual existence of others on the feelings and the behavior of the individuals [100]. Social influence is one of the areas that is studied by social psychology, and Kelman [101] defined the processes of attitude changes as a result of social influence as compliance, identification, and internalization which can be extended to include other types such as conformity [91] and self-fulfilling prophecy [102]. Considering the social influence, we introduced trust pressure and trust sensitivity, which have the power of altering the behavior of the actors.

Trust pressure has two primary sources, which are (i) the demonstration of the pressure by the community through ratings, and (ii) the effectiveness of that pressure on a specific participant. We call the pressure created by the community generated trust pressure and denote as $P_{gen}$. This pressure is created by the average trust of the community as shown in Eq. 3 where $T_r^A$ is the trust of the current community to actor A at round r and the community is the current participants of the decision making. In Eq. 3, $T_r^A$ is calculated by averaging the impressions of other actors that actor A received until the round r filtered by the confidence threshold of 0.5. In other words, we iterate over the set $N_r$ which represents the actors in the current decision making that rated A and average their impressions if they have confidence of 0.5 or more where $m$ and $c$ is defined in Eqs. 1 and 2. Since it is defined as the average of the impressions, which are values between 0 and 1, $T_r$ would also be in that interval.

$$T_r^A = \frac{\sum_{i}^{N_r} m_{X_i:A}^r}{N_r} \text{ where } c_{X_i:A} > 0.5$$

Participants may have different prospected trust values that they want to achieve. Therefore, $P_{gen}$ can be defined as the distance from $T_r$ to the target
trust of the actor, denoted as $T_{\text{target}}$, as shown in Eq. 4. Since the trust pressure is the difference between the current and the target trust, and the current trust is less than or equal to the target trust, the interval for trust pressure becomes $[0, 1]$.

$$P_{\text{gen}} = T_{\text{target}} - T_r$$  \hspace{1cm} (4)

In addition to target trust, actors may have a different attitude while adapting their behavior due to trust pressure. In other words, the same distance, $T_{\text{target}} - T_r$, can be interpreted differently. We introduce trust sensitivity, denoted by $S_T$ and in $[0, 1]$, which leads participants to this differentiation. If they are highly sensitive, with $S_T$ close to 1, they are prone to increase their trust faster than the actors with lower sensitivity even with the same trust pressure of the community. Trust sensitivity is a parameter of the actor profile, captures the actor behavior, and defined in $[0, 1]$ where 0 is the lowest, and 1 is the highest sensitivity. We define effective trust pressure, denoted as $P_e$, as the multiplication of generated trust pressure, $P_{\text{gen}}$, with trust sensitivity, $S_T$, as shown in Eq. 5.

$$P_e = P_{\text{gen}} \times S_T$$  \hspace{1cm} (5)

Effective trust pressure, $P_e$, is used to determine whether an actor proposes a new solution during the round or insists on the previous solution. If the most recent solution of hers is mostly acceptable by the community, there is no or little trust pressure generated. Therefore, she does not necessarily propose a new solution. Similarly, even if there is a generated pressure, trust sensitivity can cause a less effective pressure, as shown in Eq. 6 where $P_{\text{Threshold}}$ is an application-specific threshold value for trust pressure, which also results in absence of new solutions. Otherwise, actors propose the next solution that has less profit but more environmental value resulting in more trust and less generated and, therefore, effective trust pressure.
\[ P_e < P_{\text{Threshold}} \quad (6) \]

3.3. Solution Trustworthiness

In some applications of our trust framework, actors propose solutions and receive feedback from the community which turns into trust. In these applications, the framework also provides another metric which is called solution trustworthiness. As shown in Eq. 7, trustworthiness of a solution is calculated as the average of the ratings weighted by the impression of the raters. Proposers of the solution are also included in the equation, and they are considered as they have given a rating of 1. In Eq. 7, \( TW_s \) is the trustworthiness of solution \( s \), \( PRO \) is the set of proposers, \( RATE \) is the set of raters, \( T^i \) is the average trust of actor \( i \) defined in Eq. 3, and \( R^s_i \) is the rating given to solution \( s \) by actor \( i \).

\[
TW_s = \frac{\sum_{i}^{PRO} T^i + \sum_{i}^{RATE} R^s_i}{\sum_{i}^{PRO} T^i + \sum_{i}^{RATE} T^i} \quad (7)
\]

4. Game Theory Approach for Consensus

In game theory, backward induction can be used, specifically for perfect information games, by players to maximize their payoffs. When we consider the game tree, the last player selects the leaf, which would give him the highest outcome. Since we assumed that the previous player also knows which leaf is going to be selected by the last player, he can play according to this knowledge. This can go up to the root of the tree where the first player moves [103, 104].

We can define the payoff function as the weighted average of the trust of an actor and his direct interest from the solution he proposed. The interest that an actor gains from a solution is known by the actor; however, he may not estimate the feedback, therefore his new trust, before he receives the feedback, that is ratings, from the community. As we defined trust sensitivity, \( S_T \), previously, we propose that it can be the weight of the trust in the payoff, which means that actors with high trust sensitivity put more weight on the trust than their share.
If we assume the decision making is a perfect information game where actors can predict the ratings and their prospected trust for their proposals, they can propose the solution with the best combination of trust and direct interest. They would be reluctant to change their proposals with maximum payoff unless there is a penalty or an update in their optimizations. However, this may not necessarily be a consensus point.

In a realistic scenario, participants do not know how much trust they can get as a result of their proposals. Therefore, the proposed solutions are based on the estimation of the rating characteristics, that is strategy in game theory, of other actors. Once they have an update on their estimate of the ratings and the trust, they update their proposals in the next round.

**Type I: Basic Scenario.** In the basic scenario, the total amount of resource each participant asks for is less than or equal to the total amount of resource available as shown in Eq. 8 where \( s \) is an actor, \( S \) is the set of all actors, \( u_{a,b} \) is the amount that actor A gives actor B in his solution, and \( U \) is the total amount of resource. In this case, there is no need for negotiation, and each actor can get the amount of resources they ask for. Eq. 8 is also a consensus formula for finite and continuous resource sharing where a consensus is defined as a state in which all the actors’ requests can be satisfied. This consensus definition is different than other systems designed for opinion dynamics [31] since the actors are not required to propose the same solution.

\[
\sum_{s \in S} u_{s,s} \leq U \quad (8)
\]

**Type II: Share is important.** In this scenario, the sum of the amounts that each actor demands in their solutions is strictly greater than the available amount as in Eq. 9. In this case, there is no settlement at the beginning. Therefore, they need to negotiate to reach a consensus satisfying the condition in Eq. 8.

\[
\sum_{s \in S} u_{s,s} > U \quad (9)
\]
In this scenario, the payoff is primarily based on the resource actors receive and secondarily based on the trust, as shown in Eq. 10. Thus, an actor who wants to maximize his benefit needs to maximize his share first and then maximize his trust. For simplicity, we used the most recent measurements of the trust, that is the ratings in the most recent round. In Eq. 10, \( s_i \) is actor \( i \), \( F_{s_i} \) is the payoff of \( s_i \), \( w_s \) and \( w_r \) are the weights of share and ratings, \( u_{s_i} \) is the share of \( s_i \), and \( f_r \) is the function that determines the effect of ratings to the payoff. Since the sum of the weights, total available resource, and the highest rating is defined as 1, the range for payoff functions becomes \([0, 1]\).

\[
F_{s_i} = w_s u_{s_i} + w_r f_r \mid w_s >> w_r
\]  

(10)

In [19] and [54], the usage of different aggregation methods such as equal and weighted averaging, probabilistic approach, maximum value, and the value with maximum confidence are discussed. It is shown that the best aggregation method that can be applied to trust can change for different data sets such as Epinions and Twitter. In [105], fairness is defined as the minimum of the ratios of the powers achieved by two users for computing networks. When this approach is extended to resource sharing problem, fairness can be defined weakly as the minimum of satisfactions which are expressed as ratings, and \( f_r \) can be defined as shown in Eq. 11 where \( s^* \) represents the current actor, \( s_i \) is an actor who rates \( s^* \), and \( R_{s_i}^{s^*} \) represents the rating from \( s_i \) to \( s^* \). We include the ratings of all the actors \( s_i \) who rates the current actor \( s^* \).

\[
f_r^{s^*} = \min\{R_{s_i}^{s^*}\}, \quad \forall s^*, s_i \in S, s^* \neq s_i
\]  

(11)

**Theorem 1.** Actors maximize their payoff when they receive the amount that they initially demanded and split the remaining resource to other actors weighted by their initial demands. By splitting based on their initial requests, an actor receives equal ratings and maximizes his payoff if Eqs. 10 and 11 hold.
Proof. Maximization problem shown in Eq. 12 can be solved by equalizing the ratings given by the other actors as in Eq. 13.

\[
\max f_r \equiv \max_{s^*, s_i \in S \& s_i \neq s^*} \min \{ R_{s_i}^* \} \tag{12}
\]

\[
R_{s_i}^* = R_{s_j}^*, \quad \forall s^*, s_i, s_j \in S, s^* \neq s_i \neq s_j \tag{13}
\]

Rating function, shown in Eq. 14, is the ratio of the resource given by the ratee to the amount that rater demanded. When there are 3 actors, A, B, and C, the decision of A in round 2 gives him equal ratings from B and C as shown in Eq. 15 where \( u_{x,y}^r \) is the amount X gives to Y in round r. Also, the sum of the shares of B and C in A’s proposal is the total amount minus his share as shown in Eq. 16, and A does not change his share in his proposal as in Eq. 17.

\[
R_{s_i}^* = \frac{u_{j,i}}{u_{i,i}} \tag{14}
\]

\[
\frac{u_{a,b}^2}{u_{b,b}} = \frac{u_{a,c}^2}{u_{c,c}} \tag{15}
\]

\[
u_{a,b}^2 + u_{a,c}^2 = U - u_{a,a}^2 \tag{16}
\]

\[
u_{a,a}^2 = u_{a,a} \tag{17}
\]

When we solve the Eqs. 15 and 16, we can get the results which are basically the shares that actor A should give B and C in the second round to maximize his profit as shown in Eqs. 18 and 19.

\[
u_{a,b}^2 = \frac{1 - u_{a,a}}{u_{b,b} + u_{c,c}} \ast u_{b,b} \tag{18}
\]

\[
u_{a,c}^2 = \frac{1 - u_{a,a}}{u_{b,b} + u_{c,c}} \ast u_{c,c} \tag{19}
\]
Type III: Share is comparable with ratings. In this scenario, we omit the condition in Eq. 10. Weights are now comparable; therefore, participants may give up some of their shares to maximize their payoff.

In the first round, actors propose solutions maximizing their payoff by estimating the ratings. After solutions are proposed, actors realize that consensus is not reached since more resources are utilized than the available amount as shown in Eq. 9. Then, they update rating functions such that they give lower ratings than the expectations. In the next round, actors optimize their payoff based on the new rating functions. In other words, they revise their rating estimations. As they have a trade-off between resource and trust, changing rating function also includes consensus reaching time in the trade-off. Then, their new optimized solution would give them fewer resources because they received ratings lower than their expectations. This continues until a consensus is reached.

The estimated payoff plots of actors with trust sensitivities of 0.3 and 0.6 is shown in Fig. 2. Estimated payoff is calculated by the actor using his estimations on others’ rating functions. In the first round, both actors start by proposing a solution that maximizes their payoff and then update their solutions at each round by updating the rating part of their optimization functions. The results

![Figure 2: Actors propose the solution with the highest estimated payoff at each round. On the left, more rounds are required to reach consensus when the community has actors with trust sensitivity of 0.3 than the community with actors having trust sensitivity of 0.6 on the right.](image)
showed that when actors have high trust sensitivity, they are more likely to start with a solution that is close to a consensus point. Also, they move to a consensus point faster than an actor with low trust sensitivity which results in faster consensus reaching. These curves describe the strategy of actors during negotiation in the consensus path. Actors with lower trust sensitivity are more aggressive during negotiation whereas actors with higher trust sensitivity are less aggressive.

Depending on the application, each of these categories of actors may have advantages. In our application, the actors most typically are neighbor farmers; therefore, it is primarily important for them to trust each other in the long run because some selfish decision might have long term negative consequences for all of them. Most importantly, actors with high trust sensitivity will help the community to reach its goal faster, which is quantified by the distance from a given desirable solution discussed in Sect. 5. This is a significant example of factors that might not be captured by pure algorithmic optimization techniques and require the human in the loop.

As shown in Fig. 3, the number of rounds needed to reach a consensus point decreases as the trust sensitivities of actors increase. Since we have a limit of 13 rounds, when the trust sensitivity goes below 0.2, the consensus is not reached within the round limitation of the decision making.
5. Simulations and Results

In Sect. 4, we show how actors could propose solutions for the split of a finite resource. In more complex real-life scenarios, solutions are not only a finite resource split, but they can have more parameters included. For example, in the FEW sectors, actors, including farmers and administrative people, need to make decisions regarding types and amount of fertilizers and crops planted and their environmental effects in addition to decisions related to water allocations and energy supply and demand. Because such FEW management decisions require assessment of multiple spatial and temporal parameters, it becomes difficult for one actor to find an optimum decision or a trade-off of decisions. Therefore, we precomputed a solution set where a solution includes multiple FEW decision parameters for all actors. It allows actors to select a solution from the solution set and propose it.

5.1. Simulation Details

This study involves the use of complex hydro-climatic-agrarian models to develop test scenarios of management alternatives of FEW sectors in Umatilla and Morrow counties in Oregon. While the detailed descriptions of these models are beyond the scope of this paper, readers are encouraged to refer to [11, 12] for details on these models. Considering basic economic models of irrigation and fertilization [106], we created 5 actors and used four parameters for each of the actors for groundwater allocation, surface water allocation, crop choice, and fertilizer choice. The total amount of ground and surface water have separate limits normalized to 100 units, and there are three crop and fertilizer types available. Given input parameters, underlying hydro-climatic-agrarian models were used to generate two main outputs, specifically the profit and environmental effect.

The use of genetic algorithm (GA) in the FEW nexus is relatively new, given that most of the work has mostly been devoted to investigating how to integrate areas into a comprehensive modeling framework [107, 108, 109, 110].
Using GA [111], we generated near-optimal solutions while having constraints on the resource usage. Based on [106], the fitness function is chosen as a function of profit and environmental effect. In addition, the profit is determined by the cost of irrigation and fertilizer usage and also the price of the crop and the yield where yield is a function of the crop type and irrigation.

We investigated the effect of two main parameters, which are ratings of ratings and trust sensitivity. We run several different scenarios with or without ratings of ratings. Also, we compare decision makings where actors have high, low, or a combination of high and low trust sensitivities. Besides, we also present the impact of dynamic trust sensitivity.

We simulated decision-making scenarios for 20 rounds and presented results for the change of trust values of each actor, the trustworthiness of proposed solutions, and the average distance of solutions to the center of mass where the consensus is weakly defined as the stabilized distance after 20 rounds.

We generated different distributions of actors regarding their trust sensitivity. Each decision making consisted of 5 actors. In the first batch of the scenarios, all of the actors have the same trust sensitivity ranging from 0.01 to 1. Then, we created scenarios where actors have either high (1) or low (0.1) sensitivity. We increased the number of actors with low sensitivity gradually to see the effect of the percentage of the low sensitive people in the community to decision making.

The center of mass of solutions is defined as the average of multi-dimensional solutions weighted by the trust of their proposers. Then, the distance of two solutions is defined as the Manhattan distance of two solutions regarding their dimensions.

5.2. **Base Scenario: Static trust sensitivity, no ratings of ratings**

We start with the base case where trust sensitivities are static, and there are no ratings of ratings. As shown in Fig. 4, decision making with actors who are highly sensitive to trust quickly converges such that the proposed solutions are closer to each other. When their sensitivity is decreased to 0.3, they skip propos-
Figure 4: Consensus can be reached in fewer rounds when either actors have relatively higher trust sensitivity or there are more actors with high trust sensitivity than actors with low sensitivity.

In Fig. 5, we show the trust change of each actor where all actors have trust sensitivity of 1 in one scenario and 0.3 in the other one. When they have high trust sensitivity, trust starts going up after the first round. However, when they have 0.3 trust sensitivity, it requires more rounds for actors to feel enough trust pressure on them, defined in Eq. 5.

Another significant output of the decision makings is the trustworthiness of solutions. Instead of giving just one solution as the consensus point, we calculate the trustworthiness of solutions based on the trust of their proposers. This is one of the significant aspects of our design and framework where actors consider not only their profit but also their trust because a solution proposed by a highly trusted person will have more weight when calculating the trustworthiness of solutions.
Figure 5: Based on the trust sensitivity, it can take more time for actors to propose solutions that would receive high trust from the community.

Figure 6: Actors finalize their solutions after round 8 if they high trust sensitivity and after round 16 if they have low trust sensitivity.
Figure 7: Consensus is reached relatively quickly when the trust sensitivity is dynamic.

When actors are highly sensitive to trust, they tend to propose solutions closer to each other, which also results in fewer solutions with high trustworthiness. Also, it is supposed to happen in fewer rounds. As shown in Fig. 6, they finalize their proposals after round 8 when they have high trust sensitivity but is takes 16 rounds when they have low sensitivity. Also, the trustworthiness of solutions is lower due to the lower trust of actors, which is also a result of low trust sensitivities.

5.3. Dynamic sensitivity

In this scenario, we inspect the effect of dynamic trust sensitivity where a person with low trust sensitivity can increase it during the decision making because of trust pressure, defined in Eq. 5. We increased the sensitivities by a fixed percentage until the person reaches the desired level of trust.

The impact of dynamic trust sensitivity on the average distance of solutions is shown in Fig. 7 where consensus is reached in fewer rounds compared to Fig. 4. The distance curve for the group with trust sensitivity 1 is the same since they already have the highest level. When we consider the other groups with relatively lower trust sensitivities, their distance converges more quickly.

5.4. Ratings of ratings

Including ratings of ratings increases the number of measurements for trust; therefore, the trust changes more rapidly compared to the scenario where we
only consider ratings of solutions as trust measurements. The outcome of quickly converging trust is that the actors reach their target trust in fewer rounds, which prevents them from proposing solutions that would have decreased the distance of solutions. As shown in Fig. 8, including ratings of ratings increased the distance convergence time by up to 12% because of faster trust convergence. Also, the solution trustworthiness is increased up to 50%, and the same level of solution trustworthiness is reached around 2.7 times faster than the scenario without ratings of ratings which is shown in Fig. 6.

5.5. Complexity

Complexity analysis of the proposed collective decision making framework shows that there are two main functions that are computationally complex which are the impression and confidence calculations. Assume that the number of actors is represented by \( n \) and the number of rounds in the current decision making is represented by \( r \). Impression calculation complexity is more straightforward as shown in Eq. 20 when we keep the values of the most recent impressions and the total number of measurements. Since the confidence requires a complete recalculation using all previous measurements, it has a greater time complexity as shown in Eq. 21 which can be considered as the overall time complexity.
Impression Complexity = $O(n^2r)$ \hspace{1cm} (20)

Confidence Complexity = $O(n^2r^2)$ \hspace{1cm} (21)

However, it is more reasonable to consider the time complexity of one round because the time that actors need to make the next decision is probably greater than the time required for the framework to complete the calculations. Then, we can calculate the round complexity as shown in Eq. 22.

Round Complexity = $O(n^2r)$ \hspace{1cm} (22)

Finally, the space complexity becomes the total number of ratings given throughout the decision making which is also the same as the time complexity of the impression calculation shown in Eq. 20.

6. Conclusions

We developed a hybrid Trustworthy Human-Machine collective decision-making framework to manage FEW resources. While we used algorithms to develop optimal solutions under various criteria, we included humans in the loop to make such solutions more explainable, trustworthy, and applicable by the community. We modeled several decision-making scenarios among actors in FEW fields where there is a need for a split of a finite continuous resource or discrete decisions to be made. We presented an enhanced version of our measurement theory-based trust framework where we redesigned the trust modeling for FEW and added the capability of measuring ratings of ratings, trust pressure, trust sensitivity, and solution trustworthiness.

We also proposed a game theory approach for resource sharing problems where players maximize their payoff, a function of resource, and trust. The higher the trust sensitivity a player has, the more weight he puts on his trust in his payoff function. We showed that a decision making involving players with high trust sensitivity could end with a consensus in fewer rounds.
We run simulations with different trust sensitivity distributions and presented the results for consensus reaching, trustworthiness of solutions, and trust change during the decision making. The results showed that communities with high trust sensitivity reach consensus in fewer rounds than the ones with low sensitivity. Also, we studied how the dynamics of trust sensitivity influences the speed of reaching a consensus. In addition, the use of ratings of ratings significantly increased solution trustworthiness and reduced the time required to achieve the same level of trustworthiness.

In this article, although we do not focus on malicious activities, which means that several actors provide a disruptive rating, the rating of the society can weigh them out as we have shown with various mechanisms in [63].

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