Trust-Based Game-Theoretical Decision Making for Food-Energy-Water Management

Suleyman Uslu[1], Davinder Kaur[1], Samuel J. Rivera[2], Arjan Durresi[1(✉)], and Meghna Babbar-Sebens[2]

[1] Indiana University-Purdue University Indianapolis, Indianapolis, IN, USA
{suslu,davikaur}@iu.edu, adurresi@iupui.edu
[2] Oregon State University, Corvallis, OR, USA
{sammy.rivera,meghna}@oregonstate.edu

Abstract. Decision making has been an essential aspect of the life of both individuals or organizations. We all have to face situations where we need to decide whether a daily one such as having coffee or tea in the breakfast or selecting a graduate school for Ph.D. The importance of a decision increases as the duration of the impact of its results and the number of people that are affected increases. Food-Energy-Water (FEW) is one of the fields where the impacts can stay for a long time and affect many people and areas. In this paper, we proposed a game theory-based approach for decision making among FEW actors sharing a finite amount of continuous resource where actors have different weights on their trust and the amount of share that they receive in their payoff functions. Then, we run simulations on scenarios utilizing a more realistic discrete solution set for actors. Results have shown that when actors place more weight on trust in their payoff function, they tend to propose fairer solutions that are closer to the consensus point. Also, they move towards that point faster compared to actors with low trust weight.

1 Introduction

One of the considerably essential problems that people deal with is decision making. Although the decision itself could be challenging to make, it becomes more burdensome when multiple stakeholders are included.

Food-Energy-Water (FEW) is one of the fields where the results of the decisions could be vital for a significant part of the community. Also, it satisfies the first condition, which is involving multiple stakeholders from farmers to government agencies and administrative people.

A sophisticated Decision Support System (DSS) can help actors in FEW fields by (i) organizing the development and evaluation of feedback, (ii) highlighting the supported solutions, and (iii) demonstrating the results of proposed and approved solutions.

In this study, we first have actors to propose solutions for a split of a finite continuous resource, and then we use a more realistic and sophisticated solution

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set and have actors to propose solutions from this set at each round. Solutions proposed by actors are rated by other actors, which are used as trust measurements by our measurement theory-based trust framework.

First, we propose a game theory-based approach for finite resource sharing problem. Actors try to maximize their payoffs which is a function of both the share of the resource that they receive based on the proposed solution and the trust that they receive from the community as ratings to the proposed solution.

Then, we present our DSS considering modern and primitive approaches [5,9,13–15] combined with our trust management framework. We run simulations on the realistic solution set and investigate the effect of the weight of the trust in the payoff function. Finally, we present that as actors put more weight on trust, they tend to propose solutions closer to the consensus, which decreases the number of rounds to reach an agreement.

The paper is organized as follows. In Sect. 2, background and related work regarding decision making and trust are presented. In Sect. 3, some details of the trust management framework is explained, and the formulas that are used for this study is presented. In Sect. 4, a game theory-based approach that utilizes trust is proposed, and its results are presented. In Sect. 5, considering the game theory approach, simulation of the trust management framework for realistic data and its results are presented. Then, we conclude the paper in Sect. 6.

2 Background and Related Work

In this section, we present the background and related work for decision making, trust, and its applications.

2.1 Decision Making

Economics, society, and environment are such fields that require decisions having significant impacts on people's lives; however, a sophisticated decision-making mechanism can help people to overcome the difficulty of making decisions in those fields. One example of such outcomes is the global financial crisis of 2008, where more than half of the population of the world is affected. As the world is becoming more complex, the decisions cannot be expected to stay simpler. Moreover, engaging multiple stakeholders from different fields with a different point of views, and maybe with competing goals, could make decisions even more complicated [9].

Whereas the stakeholders might have conflicting or competing objectives, they can also be experts in the field and expressing their ideas could be their primary reason to attend the decision making. Their goal, consequently, becomes reaching a consensus by idea discussion and expression, including personal development in the field. This could require multiple rounds with expression, discussion, and alteration of the ideas. In [5], minimization of modifications approach has been proposed for expert solutions.

Besides decision making, there can be other ways of conversation and communication among participants such as surveys, focus groups, interviews, workshops, and scenario analysis [6]. Also, an algorithm is designed and proposed to utilize the feedback of the actors for a sophisticated optimization [4].

2.2 Trust and Its Applications

Trust is a context-dependent concept and can be highly effective directly or indirectly in the decision making process [22–24]. Using a trust model which is capable of historic measurements could require the process to be computerized [8, 12, 16]. To measure and anticipate trust between entities of a network or members of a community, a measurement theory-based trust management framework is proposed [21]. The list of applications of this framework include stock market prediction using Twitter data and trust management of Internet of Things, in cloud computing, and for fake user and news detection [10, 17–20, 28, 29].

Several uses of trust in decision making are the transactions over the internet [7], trust-based consumer decision making models for e-commerce [11], multi-stakeholder decision-making model for water allocation problem [1], and a generic framework for consensus reaching [2]. We proposed a DSS using our measurement theory-based trust management framework for the natural resource sharing problem in FEW [26]. An advanced version of this DSS with the capability of utilizing ratings of ratings is also proposed in [25].

3 Trust Framework

A framework which is based on measurement theory is proposed to measure the trust among parties in a community [21].

In Food-Energy-Water (FEW) sectors, one candidate of the interactions that could be used to generate a trust network between actors could be the ratings that actors assign to the solutions of a specific problem proposed by other actors. In other words, when actors gather and discuss a problem regarding FEW fields and propose solutions, their ratings to the proposed solutions can be used to measure the trust between the actors in that specific field.

In [21], the two main property of the trust is described as the impression, denoted by m, and the confidence, denoted by c. Higher ratings lead to a higher impression value, whereas consistent ratings are required to achieve a higher confidence value. As a part of the trust modeling, we calculate the impression as the average of the ratings as shown in Eq. 1. Corresponding confidence can be calculated as shown in Eq. 2 where $r^{A:B}$ is a rating from actor A to actor B as one measurement.

$$m^{A:B} = \frac{\sum_{i=1}^{N} r_i^{A:B}}{N} \tag{1}$$

$$c^{A:B} = 1 - 2e \ where \ e = \sqrt{\frac{\sum_{i=1}^{N} (m^{A:B} - r_i^{A:B})^2}{N(N-1)}} \tag{2}$$

In addition to the capability of measuring trust using ratings and calculating the impression and confidence values, our framework can anticipate the trust between two entities, which are not interacted yet, through inference rules. The two inference rules we utilize in our framework are the transitivity and the aggregation. Although there are several transitivity and aggregation formulas proposed in [21], we decided to use the TP1 and AP1 which are based on the multiplication of the impression for the transitivity and the average for the aggregation as shown in Eqs. 3 and 5. Corresponding error values can also be calculated using Eqs. 4 and 6.

$$m_T^{SD} = m^{ST} \otimes m^{TD} = m^{ST} m^{TD} \tag{3}$$

$$e_T^{SD} = e^{ST} \otimes e^{TD} = \sqrt{(e^{ST})^2 (m^{TD})^2 + (e^{TD})^2 (m^{ST})^2} \tag{4}$$

$$m_{T_1}^{SD} \oplus m_{T_2}^{SD} = \frac{m_{T_1}^{SD} + m_{T_2}^{SD}}{2} \tag{5}$$

$$e_{T_1}^{SD} \oplus e_{T_2}^{SD} = \sqrt{\frac{1}{2^2}((e_{T_1}^{SD})^2 + (e_{T_2}^{SD})^2)} \tag{6}$$

4 Decision Making Using Game Theory and Trust

Specifically, for perfect information games where the strategy of all players are known by everyone, players can maximize their payoff using backward induction. Considering the game tree, which shows the possible actions of the players at each turn, the last player selects the leaf, which gives him the best return on his last turn. Since this information is also known by the other players, second from the last player would select the node in his turn where he maximizes his payoff considering the strategy of the last player. This strategy escalates from the leaves to the root of the tree where the first player takes an action [3,27].

If an actor in the decision making can decide the values of all the parameters which affect his payoff, he can easily propose a solution that maximizes his payoff. However, in real life, there can be parameters which are decided by other actors. Moreover, a trade-off can exist between the parameters that an actor decide their value and the parameters whose values are decided by other actors.

To overcome this trade-off situation and propose a solution, which is assigning values to the parameters, actors apply weights on these parameters. If a parameter has more weight, actors tend to increase the value that they assign to that parameter.

Another question arises from the situation where some of the parameters in the payoff equation cannot be assigned by the actor himself but the other actors. In perfect information games, since the strategy of others are known to the actor, he can take an action considering this information and still maximize his payoff. However, this is not the case in real-life scenarios. Every actor has their strategy, and those strategies are not necessarily known to other actors. Moreover, an actor can change his strategy even during decision making. We show our game theory approach starting with a basic scenario and then present more realistic ones.

In our decision-making scenarios in FEW fields, actors propose solutions to a split of a finite resource, give ratings for other actors' solutions, and receive a rating for their solutions. Those ratings are used to build trust between the actors. Shares in the split that is proposed by the actor are the parameter that the actor can decide directly whereas the ratings. Therefore the trust is a parameter that is decided by the other actors, maybe by the whole community collectively. The interesting point is that an actor might affect the decision of the other actors on the parameters of the second type through his decisions on the parameters of the first type. If an actor proposes a fairer solution where he might lose some of his shares, he can receive better ratings from the community, which helps him increase his trust.

Payoff function of an actor can be defined as the weighted average of his share in the split and the trust of the community he gains during the decision making as shown in Eq. 7 where F_a is the payoff of actor a, w_s is the weight of the share, w_t is the weight of the trust, s_a is the share in the split, and t_a is the trust of the actor.

$$F_a = w_s s_a + w_t t_a \tag{7}$$

In the first scenario, the sum of the shares each actor requests for themselves in their proposals is less than or equal to the available amount of the resource as shown in Eq. 8 where a_i is an actor, A is the set of actors, $s^{a_i:a_j}$ is the amount of resource a_i gives to a_j, and M is the total amount of the resource. In this basic scenario, since the resource is enough to satisfy every actor, there is no need to negotiate.

$$\sum_{a_i \in A} s^{a_i:a_i} \leq M \tag{8}$$

In the second scenario, which leads to a negotiation, the sum of the requested amounts of the resource is more than the total amount as shown in Eq. 9. Although we can assume that each actor maximizes their payoff and propose it as a solution, they cannot receive the amount that they requested due to exceeding the total resource amount.

$$\sum_{a_i \in A} s^{a_i:a_i} > M \tag{9}$$

Considering Eq. 7, we first assume that the weight on the share is much higher than the weight on the trust, as shown in Eq. 10. In other words, actors first maximize their share until they are satisfied, then maximize their trust.

$$w_s \gg w_t \tag{10}$$

Since trust is calculated historically and the previous measurements cannot be changed, to maximize the trust, actors need to maximize the ratings for the current round. If the impression is calculated as the average of the ratings, actors maximize the sum of the ratings. However, it is more realistic that they try to maximize the ratings in a fairer way such as maximizing the multiplication of the ratings as shown in Eq. 11 which leads to an effort to satisfy other actors equally.

In Eq. 11, $f_r^{a^*}$ refers to the function of ratings that the actor a^* is maximizing, A is the set of actors, and $r^{a_i:a^*}$ is the rating from actor a_i to a^*.

$$f_r^{a^*} = \prod_{a^*, a_i \in A,\ a_i \neq a^*} r^{a_i:a^*} \tag{11}$$

Since the actors try to receive equal ratings from the other actors, after they request the amount of resource that would satisfy them, they split the remaining resource among the other actors weighted by their initial requests. In Eq. 12, actor a^* receives equal rating from all other actors where a_i and a_j also belong to the actor set A and they are different then a^*.

$$r^{a_i:a^*} = r^{a_j:a^*} \mid \forall a^*, a_i, a_j \in A,\ a^* \neq a_i \neq a_j \tag{12}$$

If the rating function for actors is defined as the ratio of the received amount of resource from an actor to the requested amount, as shown in Eq. 13, and if there are 3 actors, a, b, and c, the amount of resource that actor a should give to b and c to maximize the Eq. 11 is given in Eqs. 14 and 15. This can also be generalized to n actors by changing the denominator as the sum of the requested amounts from all other actors.

$$r^{a_i:a_j} = \frac{s^{a_j:a_i}}{s^{a_i:a_i}} \tag{13}$$

$$s^{a:b} = \frac{1 - s^{a:a}}{s^{b:b} + s^{c:c}} * s^{b:b} \tag{14}$$

$$s^{a:c} = \frac{1 - s^{a:a}}{s^{b:b} + s^{c:c}} * s^{c:c} \tag{15}$$

However, in real life, the weights on the parameters are usually comparable. Actors maximizing their share first without considering the feedback from the community may prevent actors from reaching a consensus in the decision making. Therefore, we neglect the condition given in Eq. 10 and have rounds where actors propose a solution maximizing their payoff with the prediction of the ratings received from the other actors. When the consensus condition, given in Eq. 8, is not met, actors also update their rating functions, adding a multiplier that is less than 0 to the Eq. 13, to push other actors to be fairer in their proposals.

We run two different tests to see the effect of the weights on the share and the trust received from the community. In the first test, actors weight 0.3 on the trust and 0.7 on the share of the resource that they receive. As shown in Fig. 1, actors start proposing solutions as they maximize their payoff. Then, move towards to the consensus point since they cannot receive their estimated ratings from the other actors and also simply if there is no consensus, the solutions are not accepted.

When actors increase the weight of the trust, from 0.3 to 0.6, in their payoff function, they tend to start with a solution that is closer to the consensus point compared to the weight of 0.3. Also, they move towards the consensus point faster, as shown in Fig. 2.

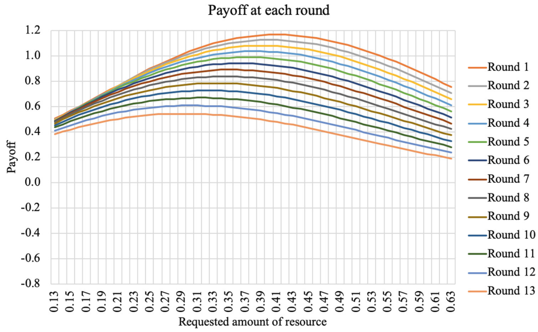

Fig. 1. When actors have 0.3 weight on the trust, they start proposing solutions away from the consensus point and also move towards it gradually.

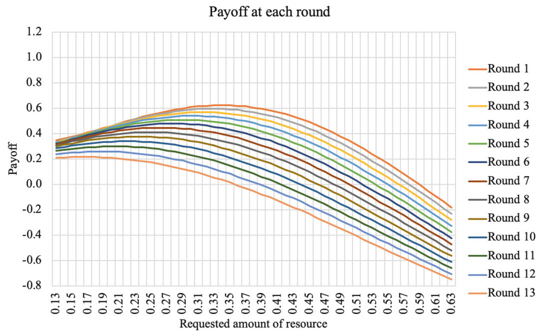

Fig. 2. When actors increase the weight of trust to 0.6, they start proposing solutions closer to the consensus point and also move towards it faster.

In Figs. 1 and 2, the curves show the payoff functions at each round. The actors propose the solution, that is the point on the curve, where the payoff is maximized.

5 Simulation and Results

In Sect. 4, we proposed game theory-based solutions for consensus reaching in a decision making for the split of a finite resource. However, real-life problems are more complex than just distributing a finite amount of resource. In FEW fields, the actors, including administrative people and farmers, need to decide the amount of water used as well as types of fertilizer and crop for a specific land. Although the water is a finite and continuous resource that they need to split, they also need to decide the other parameters.

We precomputed solutions for actors to propose during decision making. One sample solutions is given in Table 1. A solution includes values for all parameters for all actors. In our simulations, we have 5 actors, and the parameters are ground water, surface water, crop choice, and fertilizer choice.

Table 1. Sample solution for 5 actors with 4 parameters

Parameters	Actor 1	Actor 2	Actor 3	Actor 4	Actor 5
Ground water	11.4798125	35.5564315	12.8204529	21.5142238	10.1051691
Surface water	42.8265841	12.7084777	13.3468875	16.9873113	4.7743236
Crop choice	2	3	2	2	1
Fertilizer choice	2	1	3	1	1

We generated a solution set with 500 solutions that an actor can choose from. Then, we normalize the profits to [0–1] scale. Each actor sorts the solutions mostly based on their profit but using a function where the profits of other actors are also significant, as shown in Table 2, and starts proposing solutions from the first one in the sorted set.

Table 2. Normalized profits of solutions sorted for actor 1

Pro_{A1}	Pro_{A2}	Pro_{A3}	Pro_{A4}	Pro_{A5}	W_{avg}	R_{avg}
1.000	0.110	0.249	0.592	0.019	0.697	0.243
0.736	0.501	0.426	0.416	0.701	0.646	0.511
0.754	0.451	0.010	0.942	0.516	0.644	0.480
0.782	0.681	0.022	0.694	0.044	0.613	0.360

We investigated the effect of the weight of the trust in the payoff function. We generated different combinations of actors with different trust weights. In the first group of decision makings, the trust weights of actors are the same if they are in the same decision making. In the first decision making, they all weight one on the trust, which means that they want to maximize their trust first. In the other decision makings, we decrease the trust weight of all actors to 0.3, 0.1, and 0.01 to see the influence of the trust weight to the number of rounds to reach a consensus. Although we do not define the consensus point for the simulations, we provide the metric for how close the solutions are to each other. We define the average distance of solutions to the center of mass of solutions as the metric for solutions closeness where the center of mass is defined as the weighted average of the solutions where the weights are the trust of each proposer. We run the test for 20 rounds and present the results for each group.

As shown in Fig. 3, when actors have a high weight on the trust that they receive from the community, the solutions proposed by the actors converge more quickly. After they propose their first solution, they quickly realize that they can increase their payoff by increasing their trust. They propose the next solution, which gives them less resource but more to other actors, from their sorted list of solutions for the next round. Sometimes, they even skip the next one or several solutions and propose a solution that would increase their trust much higher than the next solution.

As the weight of trust decreases to 0.3, it starts taking more rounds to converge and reach some degree of consensus with a less average distance to the center of mass of solutions. When we decrease it to 0.1 or 0.01, the actors do not propose a new solution in the next 20 rounds, which jams the decision making.

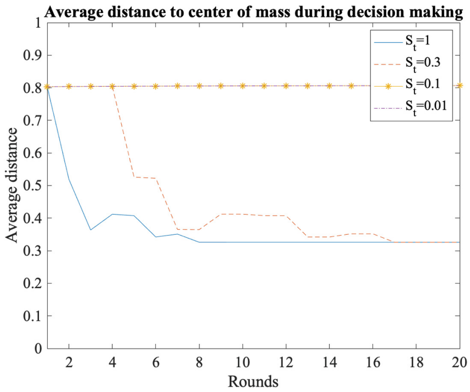

Fig. 3. When the actors have high trust weight in their payoff functions, they tend to propose a new and fairer solution and receive higher ratings which results in higher trust. Also, it leads to a faster convergence regarding the average distance of solutions to the center of mass of the all proposed solutions.

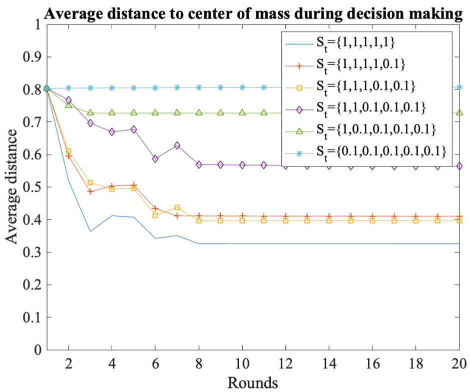

Fig. 4. When the actors have different trust weight in the same decision making, if the majority of the people has high trust weight, they can still reach an agreement level comparable to the best scenario where they all have high trust weight in a comparable number of rounds.

In addition to the first scenario, where actors in the same decision making have the same weight of trust on their payoff functions, we also investigate the effect of having a distribution of high and low weights on the trust parameter of the payoff functions as shown in Fig. 4. Starting with the case where all actors weight one on trust, we replace one actor with someone having 0.1 weight on trust.

When the number of actors with low weight on trust is 1 and 2, the average distance to the center of mass of the solutions increases, which means that the result is less acceptable. Also, it starts to require more rounds to reach that agreement level. However, both parameter, consensus degree, and number of rounds is still close to the best case where the actors have all high weight on trust. When the actors with low trust weight become the majority, the difference becomes more evident that they can be distinguished from the groups with actors where high trust weight is the majority.

6 Conclusion

In this paper, we proposed a game theory-based approach for a finite resource sharing problem considering the trust between the actors in the decision making. Actors can propose a solution maximizing their payoff regarding their share and trust by predicting the ratings they receive from other actors. When their estimations do not match the real ratings, they update their predictions and propose a new solution in the next round until a consensus is reached.

When the problem becomes more complicated than a finite resource sharing, actors can utilize a precomputed solution set to propose solutions at each round. We prepared two different scenarios. In the first one, actors have the same trust weight in their payoff functions, and there are four decision makings where actors have 1, 0.3, 0.1, and 0.01 weights on trust. In the other scenario, the actors have either high or low trust weight. We start with the group where all actors have high weight and replace a high trust weight actor with a low trust weight actor at each trial until we have all actors having low weight on trust.

Results have shown that when the actors have a high weight on trust, they tend to propose a solution that is closer to the consensus point. Also, they move towards the consensus point faster compared to actors with low trust weight. Simulations also gave us similar results. Groups of actors with high trust weight can reach a better agreement level with a smaller distance of proposed solutions. Also, they can reach a better level of agreement in a fewer number of rounds. Also, when the actors with low trust weight are the minority, the results are more comparable with the best case. However, when they become the majority, the distinction becomes more evident.

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