The Modeling and Analyzing for the Acceleration of Consensus in a Grid/Micro-Grid Organized Community

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ABSTRACT

The opinions and suggestions of diverse decision-making groups impact the formulation of regulations in the community. The grid/micro-grid system for community management fosters information exchange and enhances cohesion among residents. In this paper, the parameters of grid/micro-grid system are evaluated and integrated into a consensus model based on trust propagation and comprehensive clustering method. The model is employed to analyze the acceleration of consensus in a grid/micro-grid organized community. The experimental results illustrate that the grid/micro-grid system can effectively accelerate the consensus among decision-making groups.

Keywords: grid/micro-grid system, trust propagation, clustering

1. INTRODUCTION

As the fundamental unit of a city, community plays a crucial role in implementing government policies at the grassroots level. In recent years, the difficulty, scope, and complexity of community management have been increasing, and the requirements for emergency management have been constantly rising [1]. The grid/micro-grid system has been established to cope with these challenges, which refers to the workforce engaged in grid management, service coordination, problem identification, and reporting. The responsibilities of grid and micro-grid workers include identifying, collecting, and reporting potential issues, gathering basic information about individuals, locations, events, objects, and organizations, resolving general conflicts and disputes, and promoting public participation in grassroots social governance. Based on such community grid management, the grid/micro-grid system selects grid and micro-grid workers from the residents living in the community, who have a service-oriented mindset. They communicate and interact with residents in the corresponding grid, provide feedback on the specific needs of the residents, and also cooperate with other workers in the same community to improve the quality of community management as well as to enable individual resident directly know the public policy in a grid/micro-grid organized community [2].

Community decision-making is a crucial component during the management. In the process of community decision-making, the attitudes and opinions of different managers and community resident will be involved. It can be regarded as a large-scale group decision-making problem (LSGDM), which can manage the enormous amount of information generated during the decision-making process[3]. A common approach in managing the initial information is through the use of social networks and the trust propagation to calculate the trust level between decision-makers.

However, lack of grid/micro-grid parameters, the efficiency of trust propagation based on social networks is difficult to be determined during the process of community decision-making in a grid/micro-grid organized community. Therefore, we parameterize the grid/micro-grid system and integrate them into existing consensus model, which is beneficial for analyzing the process of trust propagation and conflict reduction during the community decision-making.

The paper is divided into five parts. Section 2 provides an overview of the basic concepts. Section 3 introduces the consensus model incorporating the grid/micro-grid system. Section 4 presents an example that estimates the achievements of consensus among decision-maker groups with or without the grid/micro-grid system. Finally, in section 5, the conclusions will be drawn.

International Conference on Smart Transportation and City Engineering (STCE 2023),
edited by Miroslava Mikusova, Proc. of SPIE Vol. 13018, 130183Y

2. THE CONCEPTS OF CONSENSUS MODEL

In this section, we explain the basic concepts related to the consensus model. First, LSGDM problem is described, which serves as the primary background of the model. Then, social network is introduced, which provides the relationship among decision-makers for such model. Finally, the method for determining the individual weights of decision-makers based on the social network within the model is presented.

2.1. The LSGDM problem

Let $DM = \{e_1, e_2, \cdots, e_m\}$ be the set of experts, and $X = \{x_1, x_2, \cdots, x_j\}$ be the opinion set provided by experts. Usually, the group is referred to as a large-scale group when $m \geqslant 20$. To understand LSGDM better, we describe the difference between GDM and LSGDM based on three points: the characteristics of experts, the clustering process, and the consensus measure[3].

In traditional GDM, the focus is typically on a limited number of experts. However, LSGDM requires a larger group size, typically with 20 or more members. Moreover, the depiction of experts in GDM as independent individuals often overlook the objective trust relationships that exist among them. However, due to the significant number of experts involved in LSGDM, this assumption rarely remains valid. Due to the complexity of LSGDM, it is challenging to address using traditional GDM methods. Therefore, expert clustering is often employed to classify experts with similar opinions into subgroups. This process effectively reduces the necessary number of experts in LSGDM and enhances consensus efficiency. The consensus measure in GDM is conducted orderly on the expert and group levels. However, to accelerate the speed of the consensus measure, the consensus measure is usually implemented at the subgroup level in LSGDM. This step avoids massive calculations on the large-scale expert level, which further improves the efficiency of consensus in LSGDM. [4]

2.2. Social network analysis

Social network analysis investigates the relationships between social members, such as group members, enterprises or countries. It can establish the relationship model between members of a group. As a useful method, social network analysis has been widely in the large-scale group decision-making problem involving groups or communities. For example, Liu, Q. Zhou, and R.-X. Ding et al[5] have employed social network models in large-scale group decision-making, proposing a formula for calculating the degree of trust among decision-makers, as well as a multi-path trust propagation algorithm based on the trust level. Zhang, Chenxi, et al [6] developed a consensus mode based on trust relationships. Zhang, Xumin, and F. Meng[7] developed a mode to select mobile health application within a hospital social network.

2.3. OWA Operators for Individual Weight Computation

Yager's OWA based procedure has been applied in the domain of individual weight computation. By considering crucial factors such as credibility, reliability, and expertise, this methodology enables the assignment of appropriate weights to elements, thereby enhancing the accuracy and effectiveness of decision-making. [8] Decision-makers weight are computed as follows:

$$w_T^{\sigma(h)} = Q\left(\frac{T(\sigma(h))}{T(\sigma(k))}\right) - Q\left(\frac{T(\sigma(h-1))}{T(\sigma(k))}\right)$$

with $T(\sigma(h)) = \sum_{l=1}^{h} TS_{\sigma(l)}, \sigma$ is a permutation such that $TS_{\sigma(l)}$ is the l-th largest value of set $\{TS_1, \ldots, TS_k\}$ and Q is a Basic Unit interval Monotone (BUM) membership function of the fuzzy linguistic quantifier to implement in the aggregation process: $Q: [0,1] \rightarrow [0,1]$ such that $Q(0) = 0,\ Q(1) = 1$ and if $x > y$ then $Q(x) \geq Q(y)$.

3. PARAMETERS OF GRID/MICRO-GRID SYSTEM

In this section, we evaluate the grid/micro-gird parameters and integrate them to the consensus model. The integration is based on two key considerations: the contact strength between decision-makers during a trust propagation process and the comprehensive clustering method. As well, the establishment of conflict network and the process of conflict reduction are demonstrated.

3.1. Determination of contact strength and individual weights

In the community management process, the trust propagation process is associated with the frequency of contact between decision-makers, which can be regarded as contact strength. For instance, community cadres supervise the work of grid staff, grid staff supervises the work of micro-grid staff, and micro-grid staff interacts directly with the community residents under their management. The frequency of contact between decision-makers varies depending on their roles within the community, which is also a vital characteristic of trust propagation. The daily work of the community is recorded in the community management system. Therefore, we have proposed a method for determining the frequency of contact between decision-makers based on the community's management mode. We export the existing work records of decision-makers over a particular time, count the number of contacts n_{ij} between different decision-makers and normalize n_{ij} to obtain the final contact strength s_{ij} among the decision-making group.

In the trust matrix of the community, decision-makers who are acquainted score each other, forming a degree of trust among decision-makers. The trust relationship tuple for e_i to e_j can be defined as follows: $\gamma_{ij} = \left(t_{ij}, s_{ij}\right)$, where t_{ij} represents the level of trust that decision-maker e_i has in decision-maker e_j. s_{ij} represents the contact strength between e_i and e_j. This gives us the initial state of the community trust matrix.

According to the formula for the multi-path trust propagation algorithm[4], we obtain the final community trust matrix T. Based on this community trust matrix, we can calculate the trust scores of decision-makers in the decision-making group, denoted as TS_i :

$$TS_i = \frac{1}{N}\sum_{j=1}^{N} t_{ji}, j \neq i \tag{1}$$

where t_{ji} represents the level of trust that e_j has in e_i.

To increase the credibility of the selection process and promote a consensus within the group, we assign weights to the decision-makers based on their trust scores. Using Yager's OWA program introduced above, the decision-maker weights can be calculated.

3.2. Decision-maker Classification

LSGDM requires a larger group size, typically with 20 or more members. In the community, there are usually multiple decision-makers with different identities and social relationships, which means a large amount of information need to be managed. Because of the complexity of LSGDM, it is challenging to manage the objective trust relationships that exist among those members. Therefore, clustering is often employed to classify decision-makers with similar opinions into subgroups.

We propose using the K-means algorithm to classify decision-makers into K subgroups, denoted by $G_k = \{G_1, G_2, \cdots, G_k\}, k \geqslant 2$. The differences between decision-makers primarily lie in their varying levels of trust in other decision-makers and in their ratings of different alternatives, which reflect conflicts of interest among decision-makers. The trust evaluation difference between two decision-makers can be defined as:

$$T\mathrm{D}_{pq} = \frac{1}{M}\sum_{s=1}^{M} \left|t_{ps} - t_{qs}\right| \tag{2}$$

where t_{ps} represents the trust level of e_p in e_s and t_{qs} represents the trust level of e_q in e_s.

The conflict of interest between two decision-makers can be defined as:

$$\mathrm{I}C_{pq} = \frac{1}{\mathrm{M}}\sum_{\mathrm{i}=1}^{\mathrm{M}} \left|v_{pi} - v_{qi}\right| \tag{3}$$

where v_{pi} represents the rating of scheme x_i by e_p and v_{qi} represents the rating of scheme x_i by e_p.

Taking into account the above two difference indicators, we define the disharmony index between two decision-makers as:

$$DI_{pq} = d(e_p, e_q) = \varepsilon \cdot TD_{pq} + (1 - \varepsilon)IC_{pq} \tag{4}$$

where ε is a variable used to control the degree of attention to the two difference indicators during the clustering process. When $\varepsilon > 0.5$, we will pay more attention to the attitudes of decision-makers towards other decision-makers for classification, while when $\varepsilon < 0.5$, we will pay more attention to the attitudes of decision-makers towards alternative schemes for classification.

Therefore, the distance between decision-maker, e_p, and group center e_c^k of G_k, can be defined as:

$$\text{dis}\,(e_p, \mathrm{G}_k) = \frac{\varepsilon \cdot \sum_{s=1}^{M} |t_{ps} - t_{cs}| + (1 - \varepsilon)\sum_{\mathrm{i}=1}^{\mathrm{M}} |v_{pi} - v_{ci}|}{M} \tag{5}$$

By implementing the K-means algorithm, we eventually obtain K subgroups, $G_k = \{G_1, G_2, \cdots, G_k\}, k \geqslant 2$. Since members in the same subgroup have similar perceptions, we can average the trust level among decision-makers and their evaluations of the scheme standards [9] to obtain the trust level and evaluation values of the subgroups using the following formula:

The trust level of subgroup G_{p} to subgroup G_{q} can be defined as:

$$\mathrm{gt}_{\mathrm{pq}} = \frac{1}{\#G_{\mathrm{p}}} \cdot \frac{1}{\#G_{\mathrm{q}}} \cdot \sum_{j=1}^{\#G_{\mathrm{q}}} \cdot \sum_{i=1}^{\#G_{\mathrm{p}}} t_{ij} \tag{6}$$

where t_{ij} represents the trust level of e_i in subgroup G_{p} to e_j in subgroup G_{q}.

The scoring of alternative schemes for subgroups can be defined as:

$$v_j^{\mathrm{k}} = \frac{1}{\#G_k} \sum_{p=1}^{\#G_k} v_{pj} \tag{7}$$

where v_{pj} represents the score given by member e_p in subgroup G_k for scheme x_j.

Based on the different scores for scheme standards among different subgroups, we can generalize the definition of conflicting interests among decision-makers to conflicts between two subgroups. The conflict of interest between subgroups can be defined as:

$$\mathrm{GIC}_{\mathrm{pq}} = \frac{1}{n} \sum_{j=1}^{n} |v_j^{\mathrm{p}} - v_j^{\mathrm{q}}| \tag{8}$$

where v_j^{p} represents the score given by subgroup G_p for scheme x_j, and v_j^{q} represents the score given by subgroup G_p for scheme x_j. To construct the conflict network between subgroups, we need to define the conflict index between subgroups. The conflict between subgroups mainly comes from the distrust between subgroup components and the conflict of interests between subgroup components. Therefore, we define the disharmony degree of subgroup components as:

$$GDI_{k_1k_2} = (1 - \mathrm{gt}_{k_1k_2}) \cdot GIC_{k_1k_2} \tag{9}$$

where $\mathrm{gt}_{k_1k_2}$ represents the trust level between two subgroups, and $GIC_{k_1k_2}$ represents the conflict of interests between two subgroups.

In addition, by using the decision-maker weights based on their trust scores calculated earlier and summing up the decision-maker weights in each subgroup, we can obtain the weight of each subgroup:

$$gw_k = \sum_{p=1}^{\#G_k} w_p \tag{10}$$

where w_p represents the trust weight of member e_p in subgroup G_k.

3.3. Conflict Network Construction and Conflict Reduction

To construct the conflict network between subgroups, we need to set the threshold θ for the disharmony index between subgroups. When the disharmony index between two subgroups exceeds this threshold, a directed edge is formed in the conflict network. Thus, the conflict network among decision-makers is as follows:

$$\mathrm{C}_\theta = \left(\mathrm{c_{ij}}(\theta)\right)_{\mathrm{k}\times\mathrm{k}}, \text{ where } \mathrm{c_{ij}}(\theta) = \begin{cases} 1, & GDI_{\mathrm{ij}} > \theta \\ 0, & GDI_{\mathrm{ij}} \leq \theta \end{cases} \tag{11}$$

Before making the final decision, we need to control the conflicting index of the conflict network within a certain reasonable threshold $\Phi(0 < \Phi < 0.5)$. We then begin the iterative process of conflict reduction by first calculating the aggregate score of the current candidate solution, which reflects the consensus of the decision groups:

$$s_j = \sum_{i=1}^{i=k} gw_i \times v_j^{\mathrm{i}} \tag{12}$$

We then select the subgroups which have conflicts with other subgroups and make modification proposals to the decision-makers e_i within them, obtaining modification proposals for their evaluations of the solution x_j :

$$v'_{ij} = v_{ij} \times (1 - \mu) + \mu \times s_j \tag{13}$$

Here, μ is in the interval $[0,1]$ and represents the degree of acceptance of the decision-maker e_i for the aggregate score. The higher the value of μ, the more the decision-maker accepts the aggregate score, and vice versa for the decision-maker who insists on their own score.

4. ILLUSTRATIVE EXAMPLE

In this section, we present an example of employing the consensus model to analyze the acceleration of consensus in a grid/micro-grid organized community.

In a community, it is going to establish work guarantee systems for grassroots officials. Two decision-making groups are involved in this task. Decision-maker Group A comprises 30 randomly selected community residents. Decision-maker Group B consists of 5 grid supervisors, 10 micro-grid workers, and 15 residents, following the community's grid/micro-grid system. Four different work guarantee systems are available for the decision-makers to choose from, denoted as $X = \{x_1, x_2, x_3, x_4\}$, where x_1 represents a system that prioritizes improving welfare benefits, x_2 represents a system that prioritizes improving salary benefits, x_3 represents a system that prioritizes controlling workload, and x_4 represents a system that prioritizes ensuring personal safety. At the same time, we set the number of mediators on the trust propagation path to no more than 1 person. To reduce most conflicts between groups and achieve consensus, set $\Phi = 0.3$.

First, we integrated the initial trust levels and the efficiency of information propagation among the decision-makers. We then executed the trust propagation algorithm, resulting in the trust matrix for decision-maker Group A as follows:

$$\begin{pmatrix} (1.00,0.00) & (\mathbf{0.99,0.78}) & & (\mathbf{0.08,0.47}) & (\mathbf{0.66,0.71}) \\ (\mathbf{0.66,0.78}) & (1.00,0.00) & \cdots & (0.14,0.00) & (0.05,0.00) \\ \vdots & & \ddots & & \vdots \\ (\mathbf{0.78,0.47}) & (0.06,0.00) & \dots & (1.00,0.00) & (\mathbf{0.16,0.52}) \\ (\mathbf{0.46,0.71}) & (0.05,0.00) & & (\mathbf{0.01,0.52}) & (1.00,0.00) \end{pmatrix}$$

And the trust matrix for decision-maker Group B is as follows:

$$\begin{pmatrix} (1.00,0.00) & (\mathbf{0.69},\mathbf{0.74}) & & (0.82,0.00) & (0.95,0.00) \\ (\mathbf{0.76},\mathbf{0.74})) & (1.00,0.00) & \cdots & (\mathbf{0.85},\mathbf{0.24}) & (\mathbf{0.78},0.96) \\ & \vdots & \ddots & & \vdots \\ (0.39,0.00) & (\mathbf{0.71},\mathbf{0.24}) & \cdots & (1.00,0.00) & (\mathbf{0.01},\mathbf{0.47}) \\ (0.84,0.00) & (\mathbf{0.46},\mathbf{0.96}) & & (\mathbf{0.07},\mathbf{0.47}) & (1.00,0.00) \end{pmatrix}$$

After executing the trust propagation algorithm, the number of direct paths connecting two decision-makers is shown in Table 1:

Table 1. Edge number.

Group	Edge Number
Group A	58
Group B	418

We can find that under the community's grid/micro-grid system, decision group B has formed a significantly larger number of direct paths compared to decision group A.

Next, we applied the conflict reduction process, which clustered decision-makers based on their familiarity and shared interests. Finally, we obtained the network conflicts for both decision-maker groups in each round, as shown in Table 2:

Table 2. Network conflict for each round.

Round	ρ_A	ρ_B
T1	0.50	0.41
T2	0.41	0.33
T3	0.33	0.25
T4	0.33	-
T5	0.33	-
T6	0.25	-

It shows that decision-maker Group B, under the grid/micro-grid system, achieved group consensus after 3 rounds of feedback, while decision-maker Group A reached group consensus after 6 rounds of feedback.

Therefore, we can conclude that in large-scale community decision-making, the application of the grid/micro-grid system can effectively reduce the number of iterations in the conflict reduction process, thus facilitating a faster achievement of group consensus.

5. CONCLUSION

In the paper, the parameters of grid/micro-grid system are evaluated and integrated into a consensus model based on trust propagation and comprehensive clustering method. By employing this model, the acceleration of consensus in a grid/micro-grid organized community is analyzed. The experimental results demonstrate that the grid/micro-grid system can effectively accelerate the consensus among decision-making groups in the community management.

The model offers several advantages, which can be summarized as follows:

- **Parameterization of the grid/micro-grid system:** Compared to generic models[5], the consensus model involves more effective information among decision-makers, including explicit community identities and social relationships, which are transformed into the parameters of the grid/micro-grid system.

- **Decision-maker grouping:** This model manages information using two features: trust propagation and conflicting interests among decision-makers. In contrast to traditional clustering models[9], this model assigns weights to both features, allowing for the generation of different-oriented.
- **Consensus method:** The model builds a conflict network between subgroups instead of decision-makers, enhancing the speed of the consensus measure.

At the same time, there are some limitations. The increasing prevalence of social media has led to the formation of highly intricate social networks among community decision-makers, which can impact the final decision outcomes. Future research aims to enhance inclusivity by involving a greater number of community residents and managing social relationships in a rational and efficient manner. By doing so, a more suitable and robust framework can be established, aligning with the dynamics of real-world social networks.

ACKNOWLEDGMENT

The authors gratefully acknowledge the contribution of City Data Information Technology Co., Ltd. in providing valuable research data for this study.

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