Trilateral Game Aided Information Management for Open Complex Giant Systems

Dewei Yang[1], Ruiyang Duan[2], Sanghai Guan[2(✉)], Jinwen Sun[3], and Huifeng Xue[1]

[1] China Academy of Aerospace Systems Science and Engineering, Beijing 100048, China
yangdwdlz@163.com, xhf0616@163.com

[2] Tsinghua University, Beijing 100084, China
duanry16@mails.tsinghua.edu.cn, guansanghai@gmail.com

[3] School of Reliability and Systems Engineering, Beihang University, Beijing 100191, China
sunjinwen@buaa.edu.cn

Abstract. Nowadays, the management and control of open complex giant systems have become a hot topic. In this paper, based on the features of network topology, nodes' heterogeneity and various information attributes, we propose a trilateral game to model the information flow management mechanism for open complex giant systems. Moreover, the players' interactions and strategies are elaborated, followed by the derivation of the subgame perfect Nash equilibrium of this game. Furthermore, we provide a toy example relying on the K-anonymity algorithm to model the degree of 'information transparency' for the information supervisors. Finally, sufficient simulation results and theoretical analysis show the efficiency and feasibility of our proposed model.

Keywords: Open complex giant system · Information management
Game theory · Trilateral game · System engineering

1 Introduction

Recently, the open complex giant system has provoked a heated discussion among the researchers in the field of the system engineering. Numerous systems can be deemed as an open complex giant system, such as the online social networks [1], Internet of things (IoT) based intelligent systems [2], the management system of a large society even of a country, etc. An efficient management and control mechanism is beneficial in terms of maintaining the "smooth" operation of aforementioned giant systems.

An open complex giant system is composed of a large number of physical or virtual nodes having different functions. Specifically, an open complex giant system has the following features: (a) Network topology: An open complex giant

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system is associated with a large network size as well as a sophisticated network topology. Also, it has few strong-connection nodes, while owns numerous weak-connection nodes in the systems, which may often lead to an asymmetric feature. (b) Nodes' heterogeneity: If mapping the system into a graph, the nodes can be classified as sensors (acquire information), actuators (process information) and controllers (supervise information) [3]. (c) Various information attributes: Information in an open complex giant system often has various attributes, which determine the depth and width of the information management.

Relying on the aforementioned statements, the open complex giant system often leads to big data acquirement, transmission as well as complex information management. Therefore, in this treatise, we focus our attention on the information flow management for open complex giant systems.

In literatures, game theory has been widely used to model the information flow management. In [4], Qiu *et al.* proposed an information management model taking into account the human impacts, such as knowledge, belief, persuasion, memory and reputation. In [5], Zhang *et al.* studied the problem of information management via evolutionary game theory to investigate the cooperative behavior among nodes with respect to the energy consumption and the network congestion. However, few treatises have considered the information management and control of the open complex giant system.

Inspired by the above-mentioned open challenges, we analyze the information flow management mechanism relying on the game theory. Our original contributions are summarized as follows:

- We propose a trilateral game for modeling the information flow management mechanism of open complex giant systems. Three kinds of players are defined. Moreover, their interactions as well as strategies are elaborated, followed by the derivation of its subgame perfect Nash equilibrium.
- K-anonymity algorithm [6,7] is first referred to model the degree of 'information transparency' for the information supervisors. Furthermore, a toy example of our proposed trilateral game is provided with respect to a concrete description.
- Sufficient simulation results and theoretical analysis show the efficiency and feasibility of our proposed trilateral game model.

The rest of this paper is organized as follows. In Sect. 2, we establish the trilateral game model and introduce its fundamental elements. Section 3 elaborates the derivation of subgame perfect Nash equilibrium considered. A toy example of our proposed trilateral game is provided in Sect. 4, followed by our conclusions in Sect. 5.

2 Trilateral Game Model

2.1 Players

The game includes three types of players: managed objects, information managers and information supervisors.

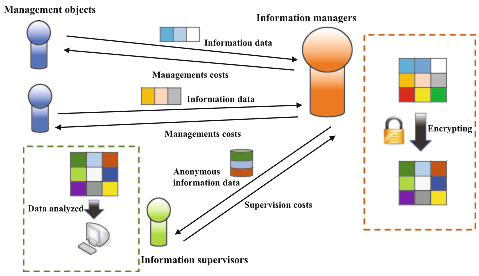


Fig. 1. A typical information flow management scenario.

Table 1. Notations

D_P	The data provided by management objects
D_M	The anonymous data provided by information managers
V_P	The value of data D_P
V_M	The value of data D_M
σ_M	The level of information transparency realized by information managers
r_M	The information supervisor's requirement of quality of data D_M
C_M	The costs of storing and modifying data D_P
C_S	The costs of analysing data D_M
P_M	The payoff to information managers
P_S	The payoff to information supervisors

- **Management Objects.** A management object provides information data to information managers and he can decide how much sensitive information he would like to provide (Fig. 1 and Table 1).
- **Information Managers.** A information manager collects information data from management objects. The information manager uses some privacy preserving data publishing(PPDP) techniques to modify the data set D_P, making sure that the level of information transparency is no less than $\sigma_M (0 \le \sigma_M \le 1)$ that he has promised to management objects.
- **Information Supervisors.** The information supervisor gets information data set D_M from information managers and then analyzes the data to improve his supervisory ability. The improvement of the supervisory ability brought by analysing the data set D_M highly depends on the value of D_M.

2.2 Payoffs

Information Supervisor's Payoff. The information supervisors improve their supervisory ability by analysing the data set D_M, the higher value of D_M, the more improvement, thus the income can be defined as:

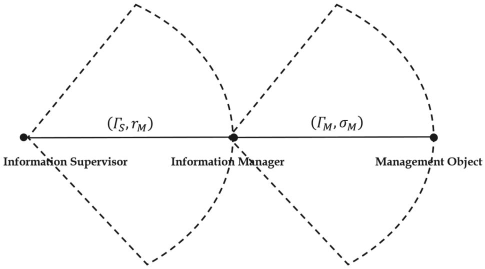


Fig. 2. The game strategy tree.

$$S_{income} = f_S(V_M), \tag{1}$$

where $f(\cdot)$ is an increasing function of V_M. Also $f(\cdot)$ can be customized to fit the characters of different applications.

$$S_{expenditure} = g_1(V_M; \Gamma_S) + C_S, \tag{2}$$

where $g_1(\cdot; \Gamma_S)$ is a parametric function and C_S denotes a fixed cost of analysing the data V_M. The information supervisor needs to input more supervisory costs to get more valuable data, so $g_1(V_M; \Gamma_S)$ is an increasing function of V_M. Each combination of the parameter Γ_S and the minimum requirement r_M is a strategy of supervisors. Therefore the payoff to the information supervisor is defined as:

$$P_S = f_S(V_M) - g_1(V_M; \Gamma_S) - C_S. \tag{3}$$

Information Manager's Payoff. The improvement of information manager's management ability depends on the intensity of supervision, here we assume that the improvement is proportional to supervisory costs, hence the income of information manager can be defined as:

$$M_{income} = C \cdot g_1(V_M; \Gamma_S), \tag{4}$$

where C denotes as the gain factor. The expenditure of information manager consists of two parts:

$$M_{expenditure} = g_2(V_P; \Gamma_M) + C_M, \tag{5}$$

where the parametric function $g_2(V_P; \Gamma_M)$ denotes the management costs spend on management objects and C_M denotes a fixed cost of storing and modifying the data D_P. The information manager need to input more management costs to for higher V_P of D_P. The parametric function $g_2(V_P; \Gamma_M)$ is an increasing function of V_P. Therefore the payoff to information manager is defined as:

$$P_M = C \cdot g_1(V_M; \Gamma_S) - g_2(V_P; \Gamma_M) - C_M. \tag{6}$$

The information manager use some PPDP methods to modify data set D_M to guarantee the promised information transparency level σ_M. And higher σ_M will lead to decrease in V_P, and we use L_{σ_M} to denote the decrease:

$$V_M = V_P - L(\sigma_M). \tag{7}$$

Each combination of Γ_M and σ_M is a strategy of information manager. The information manager's strategy will influence management object's decision and indirect affect V_P, we model this relation as follows:

$$V_P = f_P(\Gamma_M, \sigma_M), \tag{8}$$

where $f_P(\Gamma_M, \sigma_M)$ is an increasing function of σ_M. Plugging (7) and (8) into (6), the final form of payoff to information manager is:

$$P_M = C \cdot g_1(f_P(\Gamma_M, \sigma_M) - L(\sigma_M); \Gamma_S) - g_2(f_P(\Gamma_M, \sigma_M); \Gamma_M) - C_M. \tag{9}$$

2.3 Game Rules

The information supervisor first makes an offer (Γ_S, r_M) to information manager, then the information manager makes his offer (Γ_M, σ_M) to management objects, finally each management object makes a response to the offer. The extensive form of this sequential is shown in Fig. 2. The game is terminated if the information supervisor's payoff or the information manager's payoff is less than zero. The goal of the game is to maximize P_M and P_S.

3 Subgame Perfect Nash Equilibrium

The interaction between information managers and information supervisors is modeled as a finite sequential game with complete and perfect information, hence we can use backward induction to find the game's subgame perfect Nash equilibrium.

3.1 Equilibrium Strategies of Information Managers

Suppose that the information supervisor makes an offer (Γ_S, r_M), the information manager finds his optional action by solving the following constrained optimization problem:

$$\begin{aligned} \max_{(\Gamma_M, \sigma_M)} & [C \cdot g_1(f_P(\Gamma_M, \sigma_M) - L(\sigma_M); \Gamma_S) - g_2(f_P(\Gamma_M, \sigma_M); \Gamma_M) - C_M] \\ s.t. \quad & 0 \le \sigma_M \le 1, \\ & f_P(\Gamma_M, \sigma_M) - L(\sigma_M) \ge r_M. \end{aligned} \tag{10}$$

If the optimal action (Γ_M^*, σ_M^*) exists and the corresponding payoff P_M^* is greater than zero, then the information manager accepts the offer and sends his strategy (Γ_M^*, σ_M^*) to management objects. Otherwise, the information manager rejects the offer and the game terminates.

3.2 Equilibrium Strategies of Information Supervisors

Suppose that the information manager accepts an offer $(\mathit{\Gamma}_S, r_M)$ and chooses his optimal response $(\mathit{\Gamma}_M, \sigma_M)$, then the optimal strategy of the information supervisor can be found by solving the following optimization problem:

$$\begin{aligned} &\max_{(\mathit{\Gamma}_S, r_M)} [\widetilde{f}_S(V_M^*) - \widetilde{g}_1(V_M^*; \mathit{\Gamma}_S) - C_S] \\ &s.t. \quad \widetilde{f}_S(V_M^*) = f_S(f_P(\mathit{\Gamma}_M^*, \sigma_M^*)) - L(\sigma_M^*), \\ &\qquad \widetilde{g}_1(V_M^*; \mathit{\Gamma}_S) = g_1(f_P(\mathit{\Gamma}_M^*, \sigma_M^*)) - L(\sigma_M^*; \mathit{\Gamma}_S). \end{aligned} \tag{11}$$

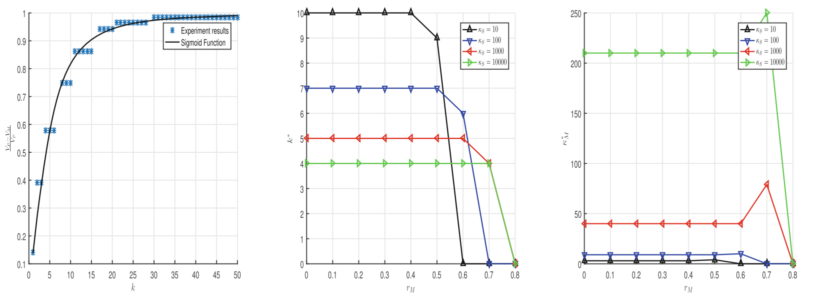
We denotes the optimum solution to above problem as $(\mathit{\Gamma}_S^*, r_M^*)$, if the corresponding payoff P_S^* is greater than zero, then $(\mathit{\Gamma}_S^*, r_M^*)$ is the supervisor's optimal strategy. If both P_S^* and P_M^* exist and are greater than zero, then the solution $[(\mathit{\Gamma}_S^*, r_M^*), (\mathit{\Gamma}_M^*, \sigma_M^*)]$ is the optimal strategy to achieve subgame perfect Nash equilibrium.

4 A Toy Example Relying on K-Anonymity

In this section, we choose K-anonymity as a specified PPDP method adopted by the information manager to change the degree of information transparency. According to the principles of K-anonymity, the information manager modifies the value of quasi-identifiers in original data table to make sure that every tuple in the anonymous table is indistinguishable form at least $k-1$ other tuples along the quasi-identifiers.

4.1 Game Model

We assume that the data set D_P has N tuples and each tuple corresponds to one management object. Every tuple consists of M attributes and every attribute



(a) The information loss. (b) Simulation Results with k. (c) Simulation Results with κ_M.

Fig. 3. Simulation results

is allowed to have null value. Suppose that the total number of management objects is fixed, denoted by N_0, and that the data set D_0 is provided by N_0 management objects and contains non null value. Then the data set D_P can be seen as the product of replacing some entries of D_0 with null values. The total value of D_P will decrease with the growth of numbers of replaced entries. We use $V_0 \triangleq V(D_0)$ to represent the value of data set D_0, and the value of D_P can be defined as:

$$V_P = V_0 \cdot (1 - \eta_{null}), \tag{12}$$

where η_{null} is the percentage of null values in D_P. As defined in (8), V_P is dependent on the information manager's strategy, which means η_{null} is determined by (Γ_M, σ_M). Here we assume that the management costs spend on management objects is proportion to the value of D_P, which means:

$$g_2(V_P; \Gamma_M) = \kappa_M \cdot V_P, \tag{13}$$

where κ_M is the gain factor and $\kappa_M \geq 1$. After introducing κ_M, η_{null} can be determined by κ_M and σ_M:

$$\eta_{null} = f_t(\kappa_M, \sigma_M). \tag{14}$$

Considering that $0 \leq \eta_{null} \leq 1$ and η_{null} should decrease as κ_M and σ_M increase, we define $f_t(\cdot)$ as follows:

$$f_t(\kappa_M, \sigma_M) = (1 - \sigma_M)^{\log_{10} \kappa_M}. \tag{15}$$

Plugging (15) and (14) into (12), V_P can be expressed as follows:

$$V_P = V_0(1 - (1 - \sigma_M)^{\log_{10} \kappa_M}). \tag{16}$$

Supposed that the information manager replaces the null entries in D_P with the most common value of the corresponding attribute, the resulting data set is then modified to D_M using K-anonymity methods. According to K-anonymity rules, for a given k ($k \geq 1$), the probability of a tuple in D_M being re-identified is less than $1/k$. Hence the information transparency level σ_M can be defined as:

$$\sigma_M = 1 - \frac{1}{k}. \tag{17}$$

The information manager can change the value of k to change the information transparency level. To find the quantitative relation between k and information loss, we carried out anonymization experiments on a real data set and found that the information loss appears to be a piecewise function of k. If k is large enough, the information loss is almost invariant with k. Therefore we choose a sigmoid function to model the relation between k and $(V_P - V_M)/V_P$ (see Fig. 3):

$$\frac{V_P - V_M}{V_P} = \frac{k}{\sqrt{k^2 + \tau}}, \tag{18}$$

where τ is a constant and $\tau > 0$. For simplicity, we use $\log k$ to replace k in (18) to slow down the increase of information loss with k. Also we set τ to 50 to make the range between 0 and 0.5, then (18) can be rewritten as:

$$\frac{V_P - V_M}{V_P} = \frac{\log k}{\sqrt{(\log k)^2 + 50}}. \tag{19}$$

The relation between V_M and V_P is now clear:

$$V_M = V_P(1 - \frac{\log k}{\sqrt{(\log k)^2 + 50}}). \tag{20}$$

Similar to (13), we assume that the supervisory costs spend by information supervisors is in proportion to V_M:

$$g_1(V_M; \Gamma_S) = \kappa_S \cdot V_M, \tag{21}$$

where κ_S is the gain factor and $\kappa_S > 0$. For a given offer (κ_S, r_M), the information manager will find the best combination of κ_M and k to maximize his payoff:

$$P_M = \kappa_S V_M - \kappa_M V_P - C_M. \tag{22}$$

Also the optimal strategy (κ_M^*, k^*) should satisfy:

$$V_P^* = V_0(1 - k^{-log_{10}\kappa_M}). \tag{23}$$

If the maximum payoff P_M^* is large than zero, then the information manager makes an offer $(\kappa_M^*, 1 - 1/k^*)$ to management objects.

Information supervisors improve their supervisory ability by analysing data set D_M.

$$S_{income} = f_S(V_M) = \beta_S V_M, \tag{24}$$

where β_S is a constant and $\beta_S > 0$. Then the payoff to the information supervisor can be defines as:

$$P_S = \beta_S V_M - \kappa_S V_M = (\beta_S - \kappa_S)V_M = (\beta_S - \kappa_S) \cdot f_r, \tag{25}$$

where V_M is determined by the information manager's strategy (κ_M, k), which is actually dependent on the information supervisor's strategy (κ_S, r_M) and $f_r(\cdot)$ denotes the relation between V_M and (κ_S, r_M). The information supervisor searches his optimal strategy to maximize the above payoff.

Deriving the analytical form of κ_M^*, k^*, κ_S^*, r_M^* is complicated. Here we only choose several specific values of κ_S and r_M, and conduct numerical simulation in Matlab to find the optimal strategy (κ_M^*, k^*) for each combination (κ_S, r_M). For simplicity, we set $V_0 = 1$, $C = 1$, and $C_S = C_M = 0$. Figure 3(b) and (c) show the simulation results, the value "0" means that the information manager fails to find a meaningful strategy (i.e. $P_M > 0$, $P_S > 0$).

Based on the results shown in Fig. 3(b) and (c), we can observe that:

- As κ_S increases, the number of "0" decreases. It means that the information manager will release data of higher quantity and quality, which is beneficial for improving supervisory ability.
- As κ_S increases, the value of k^* decreases. It means that while making less effort to protect the management objects' privacy, the information manager has to spend more management costs to get a data set of desired quantity and quality.
- For a given κ_S, the optimal strategy (κ_M^*, k^*) is almost invariant with r_M. This implicates that the maximum of P_M can be reached at one certain point. Although the increase of r_M will narrow the search space, the maximum point will always be included, as long as r_M is not too high.

5 Conclusions

In this paper, we studied the management and control for open complex giant systems. First of all, we proposed a trilateral game to model the information flow management mechanism. Secondly, we presented the subgame perfect Nash equilibrium of our proposed game. Furthermore, we provided a toy example based on the K-anonymity algorithm to model the degree of 'information transparency' for the information supervisors, followed by sufficient simulation results and theoretical analysis.

References

1. Jiang, C., Chen, Y., Liu, K.R.: Evolutionary dynamics of information diffusion over social networks. IEEE Trans. Sig. Process. **62**(17), 4573–4586 (2014)
2. Jiang, C., Zhang, H., Ren, Y., Han, Z., Chen, K.-C., Hanzo, L.: Machine learning paradigms for next-generation wireless networks. IEEE Wirel. Commun. **PP**, 2–9 (2016)
3. Wang, J., Jiang, C., Quek, T.Q.S., Wang, X., Ren, Y.: The value strength aided information diffusion in socially-aware mobile networks. IEEE Access **4**, 3907–3919 (2016)
4. Qiu, W., Wang, Y., Yu, J.: A game theoretical model of information dissemination in social network. In: International Conference on Complex Systems, pp. 1–6 (2012)
5. Zhang, J., Gauthier, V., Labiod, H., Banerjee, A., Afifi, H.: Information dissemination in vehicular networks using evolutionary game theory. In: 2014 IEEE International Conference on Communications, Sydney, Australia, pp. 124–129 (2013)
6. Sweeney, L.: k-Anonymity: a model for protecting privacy. Int. J. Uncertainty Fuzziness Knowl. Based Syst. **10**(05), 557–570 (2002)
7. Xu, L., Jiang, C., Wang, J., Yuan, J., Ren, Y.: Information security in big data: privacy and data mining. IEEE Access **2**, 1149–1176 (2014)