

## Chapter 2

# Optimal Allocation of Decision-Making Authority in IoT-Based Manufacturing Enterprises

### 2.1 Introduction

Global economic integration and information network have brought radical changes to the operational management of business processes. Emerging information technologies, such as the Internet of Things (IoT) and big data, have fostered customers' changing personalized demands and accelerated the product updating speed, thereby impacting traditional production patterns. Empirical studies found that the IoT infrastructure can effectively support information systems of next-generation manufacturing enterprises [28]. More specifically, the requisition and sharing of a product's life cycle (e.g., market demand, usage, and recycling) information in an IoT-based manufacturing enterprise have the following advantages over traditional manufacturing scenarios: (1) more comprehensive acquisition of product life cycle information, which would be impossible in a traditional manufacturing environment, (2) precise detection and analysis of on-site data through the perceptual and application layers of the condensed sensing network, and (3) faster information transmission in an intelligent manufacturing environment, so different hierarchies can conveniently access the needed information.

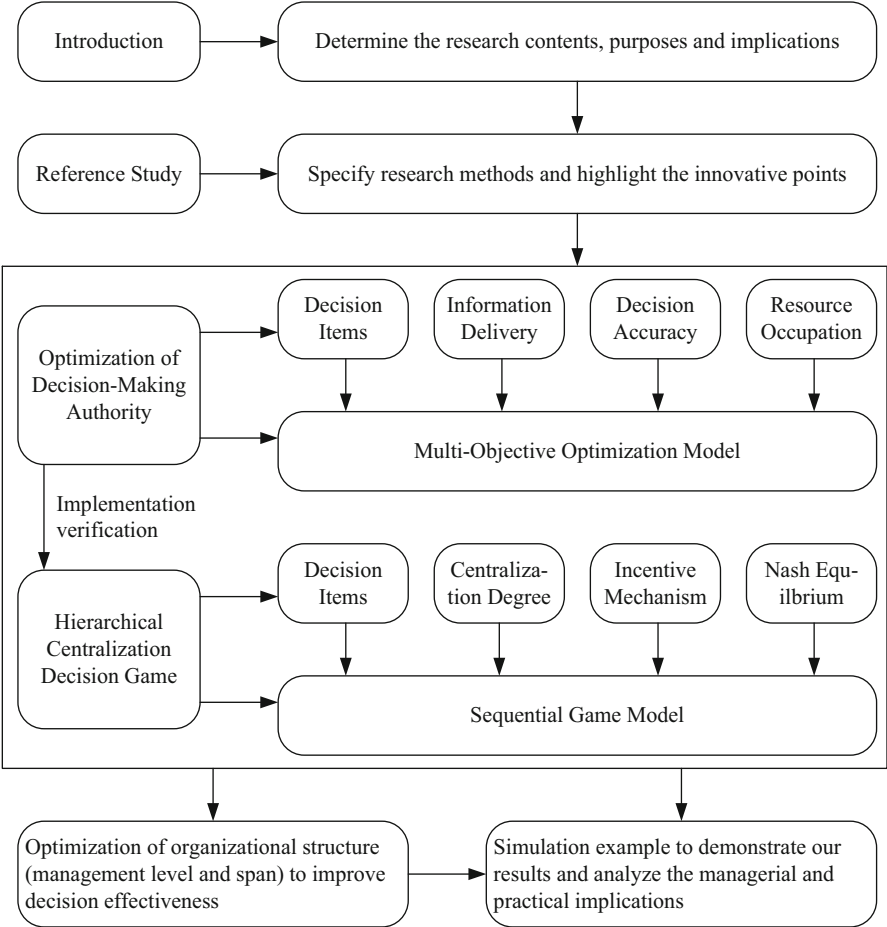
Scholars have studied the adoption mechanisms of RFID technology and found that it can practically improve manufacturing efficiency [29, 30]. However, few considered the adjustment of the internal governance structure from the perspective of decision-making authority optimization, which may lead to heterogeneous firm performances. To survive fierce market competition, managers must focus on the decisions they make when facing the intricate options offered by their cooperative partners, manufacturing strategies/tactics, and operational skills [31]. Accordingly, a reasonable distribution of enterprise resources is required. For instance, human resources can combine personal experience and knowledge with IoT data to make quick and accurate decisions. We should thus comprehensively consider information transmission, knowledge occupation, and organizational resources when

making effective decisions [32]. Such types of organization include flexible business alliances, market-oriented virtual enterprises, and long-term strategic networks.

Decision efficiency is of such vital importance to enterprises that decision errors in key areas can result in severe losses [33]. Rapid decisions contribute to enterprises' agility and flexibility in seizing transient market opportunities and the improvement of the customer experience, while decision accuracy is another guarantee of success. While highlighting the importance of rapid and accurate enterprise decision making, recent studies have systematically proposed various skills or abilities professional managers should master, or performed analysis about frequent decision errors to support the improvement of decision efficiency [34]. In this chapter, we focus on the allocation structure of decision-making authority in an IoT-based manufacturing enterprise that considers both decision speed and accuracy by matching decision items with resource occupations. A game theory model is then put forward concerning a specific organization level to demonstrate to what extent the optimal allocation of the decision authority can be implemented. After that, we discuss how decision-making efficiency is affected by organizational change, e.g., management levels and span.

Manufacturing enterprises will inevitably be challenged by numerous decision items with different degrees of emergency and importance in operational processes. The organizational designer considers the decision items and makes a trade-off to regulate its structure and policy [35]. This chapter develops a satisfactory allocation mechanism for the decision-making authority and an evaluation method of the decision efficiency in an IoT-based manufacturing enterprise under the framework of a multi-objective optimization model. The objectives of our optimization model are to minimize the total expected loss of unscheduled decision items, maximize the total decision benefits, and minimize the maximum completion time of decision items. Based on analyses of existing studies, the application of information technology does not necessarily lead to the decentralization or flattening of the organizational structure. Rather, decentralization can result in the decline of the service level, management control level, and ever-increasing manufacturing costs [36]. Our game theory model analyzes the evolutionary trend of centralization toward different types of decision items in each organizational level from a microcosmic point of view. In addition, we also analyze how the allocation mechanism of the decision-making authority changes with the organizational structure in an intelligent manufacturing environment. Figure 2.1 shows the framework and technical outline of this chapter.

The hierarchical centralization decision game model in Fig. 2.1 was proposed to analyze to what degree different levels should reveal their centralization toward the various decision items for the purpose of personal benefit maximization. We verified if the optimal decision-making authority allocation solution can be fully implemented through the sequential game model. We also developed an effective incentive mechanism for the implementation of the optimal solution and proposed suggestions for organizational change in an intelligent manufacturing environment. The main contributions of this chapter can be concluded as follows:



**Fig. 2.1** The framework and technical route of the current chapter

(1) we put forward optimization methods for the quantization of the decision-making authority, which can further be extended to the internal governance of the organizational structure; (2) our results are meaningful for IoT-based manufacturing enterprises to improve their decision efficiency and cultivate core competitiveness, thus ensuring flexibility and adaptation toward changing market opportunities; and (3) the models established here are closer to actual manufacturing practices since the main technical advantages of the IoT are refined and taken into consideration.

The rest of this chapter is organized as follows. Section 2 reviews some recent literature related to this work and highlights our innovative points. The multi-objective optimization model of decision-making authority allocation is established in Sect. 3. Section 4 further discusses the optimal centralization degrees of each organization level toward different types of decision items. The effects of

organizational change on the decision effectiveness are considered in Sects. 3 and 4. Our results are also demonstrated in a numerical example. Finally, we discuss and summarize the conclusions of this chapter and put forward some suggestions for further study.

## 2.2 Literature Review

With the development of emerging information technology, recent research has sufficiently considered the new operating characters and information transmission problems under manufacturing environment or in supply chain management. Yan and Huang [37] indicated that the application of RFID technology in supply chain management can help enterprises to share information and get out of the “bullwhip effect.” They proposed an IoT-based supply chain information transmission model for better information transmission and satisfy demands of both enterprises and customers. By extending the IoT to manufacturing field, Zhang et al. [38] presented a real-time information capturing and integration architecture of the Internet of Manufacturing Things (IoMT). A real-time manufacturing information integration service (RTMIIS) was also designed to achieve seamless dual-way connectivity and interoperability among enterprise layer, workshop layer, and machine layer. Li et al. [39] provided a theoretical framework which classifies IoT strategies into four archetypes from two dimensions of manager’s strategic intent and industrial driving force. They found that industry information sharing can efficiently contribute to the enhancement of market-based and technology-based exploratory and exploitative capabilities. Inspired by these studies, the information delivery and sharing within IoT-based enterprises are considered faster, more accurate, and comprehensive. However, we also emphasize the role of knowledge resource that support decision making through information analysis.

With respect to the organization resource, scholars stressed on different aspects according to their different research backgrounds. Kehoe and Wright [40] explored the relationships between employees’ perception of high-performance HR practice, willing to stay within the organization and citizenship behavior. The results indicated that affective organizational commitment fully mediated the relationship between HR practice perceptions and intention to remain with the organization. Tseng and Lee [41] empirically studied how firms’ knowledge management capabilities and uniquely dynamic capabilities can be applied or developed to provide quick response to the market competition. Knowledge management capabilities were found to enhancing dynamic capability of organizations and in turn increasing organizational performance and providing competitive advantages. Based on a sample of 226 Spanish firms, Beltrán-Martín et al. [42] explored the mediating variables between high-performance work systems (HPWS) and organizational performance, and that this mediating role was confirmed to be the firm’s human resource (HR) flexibility. Foss et al. [43] proposed that interactions with external knowledge sources were often involved when realizing opportunities. Their

analysis also indicated that the strength of this association was significantly influenced by organizational designs. Although occupation of organization resources including information, knowledge, and human resource were often considered in the extant literature on factors that affect performance improvement, the effects of organizational resources on allocation of decision-making authority remain to be investigated.

Decision items were often classified according to their relative degree of importance. Correct major decisions made by enterprises can intuitively generate more benefits, while more knowledge and time are required. Citroen [44] investigated how information was obtained, analyzed, judged, and applied by executives in industries that have to make strategic decisions. Moreover, the crucial role of high-quality information played in reducing uncertainty during the structured decision-making process was stressed. Ivanov [45] developed a framework to increase the efficiency, consistency, implacability, and sustainability of decisions on supply chain strategy, design, tactics, and operations, which were interlined and dispersed over different supply chain structures (functional, organizational, informational, financial, etc.). Sivak and Schoettle [46] investigated the effects of decisions that a driver can make to influence on-road fuel economy of light-duty vehicles. Drivers' decisions were classified into strategic decisions (vehicle selection and maintenance), tactic decisions (route selection and vehicle load), and operational decisions (driver behavior). Ivanov et al. [47] considered different value chain strategies as an integrated framework where supply chain management served as a basis for integration, cooperation, and coordination, with the managerial integration classified into strategic, tactical, and operative decision-making levels. Manufacturing enterprises will encounter a huge number of stochastic decision items with different importance and emergency degrees during daily management. The allocation problem of decision-making authority can be considered as a dynamic scheduling problem with random-arrival decision items. Similar to the existing literature, decision items are categorized into strategic, tactic, and operational levels. However, we consider a constant number of decision items in a certain period instead of random-arrival feature for simplification.

Intraorganizational decision mechanisms, including factors that influence the allocation of decision-making authorities, were extensively explored, and some achievements were achieved. Bester [48] studied how the preferences of the organization's members affected the optimal allocation of decision rights using a mechanism-design approach and found that decentralized control rights may enhance organizational efficiency. Harris and Raviv [49] studied an empirical model to analyze when the CEO would choose to allocate decision-making authority over an investment decision to a division manager. The probability of delegation was shown to increase with the importance of the division manager's private information while decrease with that of the CEO. On the study of authorization preferences, Graham et al. [50] investigated the degree to which executives delegate financial decisions and the circumstances that drive variation in delegation.

The authorization preferences were shown to be related to both corporate policies and personal characteristics of the executives. Colombo and Delmastro [51] focused on the determinants of the allocation of decision-making power through the estimates of ordered probit models with random effects. Factors that prominently explained the authority delegation were shown to include complexity of plants' operations, communication technologies, ownership status of plants, and nature of decisions considered. Although many factors were found to significantly influence the allocation of firm's decision-making authorities and decentralization behavior of executives, this chapter attempts to combine the optimization of organizational resources with the allocation of decision-making authorities in an IoT-based manufacturing enterprise. Particularly, the optimization model established provides a new thought for the organizational governance.

The balance of decision-making objectives and performances is another concern that practitioners focus on when facing dynamic market opportunities. The effect of strategic decision speed on subsequent firm performance was explored, and environmental and organizational characteristics that related to decision speed were identified [52]. It was proposed that strategic decision speed could mediate the relationship between environmental/organizational characteristics and performance. Moreover, fast strategic decision making implied subsequent firm profit growth and mediated the relation of dynamism, centralization, and formalization with firm performance. Bogacz et al. [53] considered the optimal decision making in two-alternative forced-choice (TAFC) tasks by analyzing six models of TAFC decision making. They concerned both decision accuracy and speed in a statistically optimal algorithm and proved that there was always an optimal trade-off between speed and accuracy that maximized various reward functions. For the inherent compromise between two or more objectives in many natural and artificial decision-making systems, Marshall et al. [54] built an optimization model to examine the trade-off between speed and accuracy and concluded that noise and time cost of assessing alternative choices were likely to be significant, which meant that increasing the willingness of individuals to change their decisions cannot improve collective accuracy overall without impairing speed. Shang and Seddon [55] focused on the benefits that organizations might achieve from their investment in enterprise systems (ES) and provided five detailed benefits of dimensions through the investment decisions. The managerial benefit of resource management and decision making was noted that accurate and time-effective information delivered to managers could improve the speed and quality of decision making and assisted with cost control. It is obvious that previous research highlighted both the accuracy and speed of decisions that managers make. Some literature also took the decision cost control or achieved benefit into consideration. The major limitation was concluded to be the secondhand data (e.g., provided by website), which was believed to be unreliable or misinterpreted. Considering the rapidly changing market opportunities, the objectives of decision-making authority allocation in this chapter include maximization of decision benefit and minimization of average decision time and

unscheduled decision items (also can be interpreted as potential loss due to unprocessed decision items).

Previous study also explored the change of organizational structure (such as organizational hierarchical and management range) in situations supported by information technologies. Further research is required to find a trade-off between decision efficiency and agent supervision costs. Dewett and Jones [56] described two principal performance-enhancing benefits of IT, information efficiencies and information synergies, and then discussed the role that IT plays in moderating the relationship between organizational characteristics (including structure, size, learning, culture, and interorganizational relationships) and organizational efficiency and innovation. Bloom et al. [57] studied the impact of information and communication technology on the autonomy and control span of plant manager. Analysis of data set of American and European manufacturing firms confirmed that advanced information technologies were associated with more autonomy and a wider control span, whereas communication technologies decreased the autonomy for workers and plant managers. Rajan and Wulf [58] investigated the relationship between reporting relationships, compensation structure, and information technology and found that firm hierarchies are becoming flatter. This meant that the number of positions reporting directly to the CEO had gone up significantly while the number of organizational levels between the division heads and the CEO had decreased, reflecting a delegation of authority. Mookherjee [59] concerned the costs and benefits of delegated decision making in hierarchical organizations or contracting networks with regard to problems of incentives and coordination. The communication costs that restrict the performance of centralized arrangements relative to delegation were introduced, which had to be traded off against possible control losses of delegation. In IoT-based manufacturing enterprises, information acquired is undoubtedly more comprehensive and accurate than traditional scenarios. The relationship between characteristics of information and decision accuracy and speed still remains to be explored. The directions of organizational transformation, or how the hierarchies or control span should be adjusted, urgently need to be investigated for IoT-based manufacturing enterprises to maximize their decision efficiency.

### **2.3 Optimization Model for Decision Authority Distribution**

Taking the advantage of the Internet of Things (IoT), manufacturing enterprises have significantly improved their operational efficiency when facing uncertain market opportunities. Recent studies gradually emphasized the application of IoT in promoting production process efficiency, while the crucial roles of “decision-making factors” in determining firms’ success were often ignored. The exploration of microcosmic governance within the enterprise, such as structure reorganization and business process reengineering, is getting recognized by the theoretical

research and manufacturing practices. This section mainly discusses the optimal allocation of the decision-making authorities among organizational hierarchies within an IoT-based manufacturing enterprise. A multi-objective optimization model is first established considering both information delivery and resource constraints with the purpose of maximizing the decision efficiency and minimizing the total decision time and the opportunity losses. We try to analyze how the allocation of enterprise's decision-making authority is affected by factors including distortion rate of decision information delivery, subjective weights of enterprise's objectives, etc. The changing tendency of enterprise's organizational structure under IoT environment is further explored compared to that of traditional manufacturing contexts. Our numerical research illustrates that the enterprise's objectives are significantly affected by the inter-layer distortion rate of information delivery, while independent from the waiting time of information delivery and the enterprise's subjective weights of objectives. The number of hierarchical level of the IoT-based manufacturing enterprise is suggested to be reduced to make a more efficient and flatter organizational structure.

### 2.3.1 The Multi-objective Optimization Model

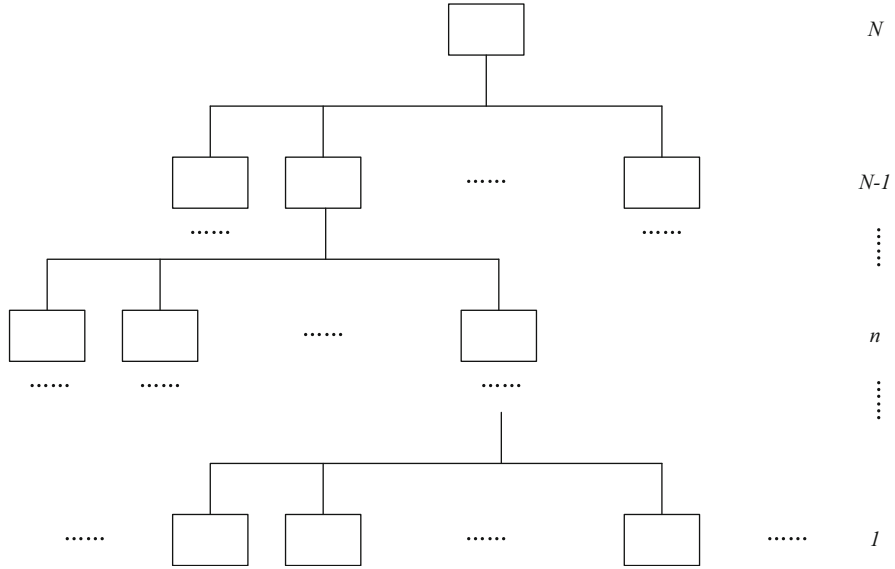
Suppose an IoT-based manufacturing enterprise faces dynamic market opportunities and has to make rapid but accurate decisions toward a total number of  $K$  decision items within a certain period of time. The decision can be made at any level of its hierarchy but have to be implemented at the basic level. We classify the decision items into three categories, including  $K_1$  strategic decision items,  $K_2$  tactic decision items, and  $K_3$  operational decision items according to their importance to the enterprise with  $\sum_{i=1}^3 K_i = K$ . Empirically, we also have  $K_1 < K_2 < K_3$ , which

means that most of the decision items the enterprise faces are operational type. Generally, the relationship between  $K_i$  ( $i = 1, 2, 3$ ) can be approximately summarized according to previous experience. In addition, we define the importance of the decision items by  $\gamma_i$  ( $i = 1, 2, 3$ ), respectively, with  $\gamma_1 > \gamma_2 > \gamma_3$ .

For the convenience of model establishment and further analysis, we assume the organization of discussed manufacturing enterprise to be inverted pyramid structure. Moreover, the differences between functional divisions are blurred and ignored. The simplified organizational structure of the enterprise is shown in Fig. 2.2. It has  $N$  hierarchical levels with the most basic staff level 1 and the top executive level  $N$ . Other hierarchical level can be represented as ( $n = 1, 2, \dots, N$ ). The average management span is defined as  $m$ , which means that each staff in level  $n$  will be directly reported to by  $m$  staffs in level ( $n - 1$ ).

Although sometimes a strategic decision item can be gradually split into several tactic or operational decision items, they are repetitively computed for the decision authority of the split tactic, or operational decision items can also be allocated.





**Fig. 2.2** The organizational structure of the IoT-based manufacturing enterprise

Moreover, we assume that each decision item can only be allocated to one staff. Instead of concerning whom in a certain level the decision authority of an item is allocated to, we only care about the average allocation condition. Let  $k_{ni}$  denote the number of item  $i$  which decision authority is allocated to level  $n$ . For instance,  $k_{11}$  means the number of strategic decision items allocated to the most basic staff. We have  $\sum_{n=1}^N k_{ni} \leq K_i$ . This means the sum of type  $i$  decision items allocated to each hierarchical level will not exceed the total number that the enterprise encountered. Besides, it is obvious that  $\sum_{i=1}^3 k_{ni}$  represents the total number of different types of decision items allocated to level  $n$ .

Under the intelligent manufacturing environment, product life cycle information can be real-time detected and transparently shared through firm's sensing network. The decision maker can get access to the accurate information he needs freely and conveniently when permitted to the intranet or information management system of the enterprise, which is the main difference compared to that of traditional scenario. It is worth noting that the decision maker will combine the information acquired with his own knowledge to make a defective decision. Since the knowledge/experience can be explained as the ability to process information, more accurate decision will be made based on abundant knowledge. Let  $f(n)$ ,  $g(n)$ , and  $h(n)$  denote level  $n$ 's knowledge on strategic, tactic, and operational decision items, respectively. Intuitively,  $f(n)$  is an increasing function of  $n$ , i.e., the knowledge of strategic decision increases with hierarchical level.  $g(n)$  is a concave function of  $n$ , i.e., the middle management level has more information on tactic decision items.  $h(n)$  is a

decreasing function of  $n$ , i.e., lower level has more knowledge on operational decision items. In addition, we have  $0 \leq f(i), g(i), h(i) \leq 1$ , with the extreme situations of no knowledge and full knowledge.

When the decision is made in level  $n$ , it will be transmitted downward to level 0 (e.g., workers) for implementation. Let  $p$  ( $0 < p < 1$ ) be the distortion rate of decision information during each transmission between adjacent hierarchical levels. The delivery time of decision information is denoted by  $s$ , namely, waiting time of decision information in every intermediate transmission level. The processing time of the decision items is defined as  $t_i$  ( $i = 1, 2, 3$ ), respectively. Since strategic decision items are generally much more complicated and require prudent treatment, we have  $t_1 > t_2 > t_3$ . Each staff in level  $n$  has an available time  $T_n$  for decision making, which can be regarded as an important organizational resource of the manufacturing enterprise. We also assume that  $T_n > T_{n+1}$ , that is, staffs in lower hierarchical level have more time available for decision making. Moreover, it is obvious that  $\sum_{i=1}^3 k_{ni} t_i \leq m^{N-n} T_n$ .

From the description above, the notations used in this section are listed in Table 2.1.

**Table 2.1** Notations of the optimization model

Notation	Description	Constraints
$K$	Total number of the decision items	—
$i$	Index of category of the decision items	$i \in \{1, 2, 3\}$
$K_i$	Number of decision items in category $i$	$\sum_{i=1}^3 K_i = K,$ $K_1 < K_2 < K_3$
$\gamma_i$	The importance of the decision items	$\gamma_1 > \gamma_2 > \gamma_3$
$N$	Total hierarchical levels of the organizational structure	—
$n$	Index of the hierarchical level	$n \in \{1, 2, \dots, N\}$
$m$	The average management span	$\sum_{i=1}^3 k_{ni} t_i \leq m^{N-n} T_n$
$k_{ni}$	The number of decision items in category $i$ allocated to staffs in level $n$	$\sum_{n=1}^N k_{ni} \leq K_i$
$f_1(n)$	Level $n$ 's knowledge on strategic decision items, an increasing function of $n$	$0 \leq f_1(n) \leq 1$
$f_2(n)$	Level $n$ 's knowledge on tactic decision items, a concave function of $n$	$0 \leq f_2(n) \leq 1$
$f_3(n)$	Level $n$ 's knowledge on operational decision items, a decreasing function of $n$	$0 \leq f_3(n) \leq 1$
$p$	Distortion rate of cross level transmitted information	$0 < p < 1$
$s$	Information delivery time in each intermediate level	—
$t_i$	Processing time of $i$ type decision item	$t_1 > t_2 > t_3$
$T_n$	Available time of each staff in level $n$ for decision making	$T_n > T_{n+1}$

From Table 2.1, we can calculate enterprises' benefit if a decision item is made and implemented. For example, the benefit is  $\gamma_1 f(n) p^n$  when a strategic decision item is made in level  $n$ . Here  $\gamma_1$  directly represents enterprise's benefit under ideal conditions. Therefore, the total benefit of the IoT-based manufacturing enterprise is given as follows:

$$TB = \sum_{n=1}^N p^n \left[ \sum_{i=1}^3 \gamma_i k_{ni} f_i(n) \right] \quad (2.1)$$

When the decision-making authority of an item is not allocated to any level, however, the enterprise will lose a market opportunity since no actions are taken. As such, the enterprise should make the best of its organizational resource to reduce the potential opportunity loss. Here  $\gamma_i$  is also used to represent the unit relative loss, and we have the total opportunity loss:

$$OL = \sum_{i=1}^3 \gamma_i \left( K_i - \sum_{n=1}^N k_{ni} \right) \quad (2.2)$$

In order to make a rapid response to the market, the optimal allocation of the decision-making authority should ensure a sufficiently short time span. The total time for decision making and transmission of decision information in level  $n$  is calculated as  $\sum_{i=1}^3 k_{ni}(t_i + ns)$ . As the number of staffs in level  $n$  is  $m^{N-n}$ , thus we have the average decision time in level  $n$ :

$$DT_n = \frac{\sum_{i=1}^3 k_{ni}(t_i + ns)}{m^{N-n}} \quad (2.3)$$

From Eqs. 2.1, 2.2, and 2.3, we can further propose the objectives of our model: (1) improve the overall level of decision accuracy to maximize the total benefit, (2) make full use of firm's resources to minimize the total opportunity loss, and (3) minimize the maximum average decision time in level  $n$ . The allocation of decision-making authority requires to be optimized to satisfy these three objectives, or in other words, the optimal  $k_{ni}$  need to be solved. Thus, the multi-objective model is shown as follows:

$$\begin{aligned}
& \max \sum_{n=1}^N p^n \left[ \sum_{i=1}^3 \gamma_i k_{ni} f_i(n) \right] \\
& \min \sum_{i=1}^3 \gamma_i \left( K_i - \sum_{n=1}^N k_{ni} \right) \\
& \min \max_n \frac{\sum_{i=1}^3 k_{ni} (t_i + ns)}{m^{N-n}} \\
& s.t. \quad k_{ni} \in D \\
& D = \left\{ k_{ni} \in \mathbb{Z}^{N \times 3} \left| \begin{array}{l} \sum_{i=1}^3 K_i = K; K_1 < K_2 < K_3; T_n > T_{n+1}; 0 < p < 1; t_1 > t_2 > t_3; \gamma_1 > \gamma_2 > \gamma_3; \\ \sum_{n=1}^N k_{ni} \leq K_i; \sum_{i=1}^3 k_{ni} t_i \leq T_n; 0 \leq f_i(n) \leq 1; \sum_{i=1}^3 k_{ni} t_i \leq m^{N-n} T_n \end{array} \right. \right\}
\end{aligned} \tag{2.4}$$

To solve the analytical solution of this multi-objective programming directly is difficult and complex. Here we declare the method and process so that we acquire its non-inferior solution. We first unify different objective functions into comparable normalized form.

Take  $\min OL(k_{ni})$  as an example, let  $OL^* = \min_{k_{ni} \in D} OL(k_{ni})$  and  $OL^\Delta = \max_{k_{ni} \in D} OL(k_{ni})$ , take the linear transformation of the objective function  $OL(k_{ni})$ , and we have

$$ol(k_{ni}) = \frac{OL(k_{ni}) - OL^*}{OL^\Delta - OL^*} \tag{2.5}$$

Similarly, the objective function  $\max TB(k_{ni})$  is equivalent to  $\min[-TB(k_{ni})]$ . Thus, we can obtain the linear transformation of  $-TB(k_{ni})$  as

$$-tb(k_{ni}) = \frac{-TB(k_{ni}) + TB^*}{-TB^\Delta + TB^*} \tag{2.6}$$

where  $TB^* = \min_{k_{ni} \in D} TB(k_{ni})$  and  $TB^\Delta = \max_{k_{ni} \in D} TB(k_{ni})$ .

With respect to the objective function of  $\min_n \max DT_n$ , let  $DT(k_{ni}) = \max_n DT_n(k_{ni})$ , and we have the linear transformation of the objective function  $\max_n DT_n$  as

$$dt(k_{ni}) = \frac{DT(k_{ni}) - DT^*}{DT^\Delta - DT^*} \tag{2.7}$$

where  $DT^* = \min_{k_{ni} \in D} DT(k_{ni})$  and  $DT^\Delta = \max_{k_{ni} \in D} DT(k_{ni})$ .

From Eqs. 2.5, 2.6, and 2.7, we turn problem (2.4) into a normalized form of multi-objective minimization problem:

$$\begin{aligned} & \min ol(k_{ni}), -tb(k_{ni}), dt(k_{ni}) \\ & s.t. \quad k_{ni} \in D \end{aligned} \quad (2.8)$$

In fact, our objectives are mutually independent. Give the weight coefficients of the normalized objectives and turn problem (2.8) into a single-objective minimization problem

$$\min w_1 ol(k_{ni}) - w_2 tb(k_{ni}) + w_3 dt(k_{ni}) \quad (2.9)$$

where  $w_1, w_2$ , and  $w_3$  are the subjective weights of the three objectives with  $w_1, w_2, w_3 > 0$  and  $w_1 + w_2 + w_3 = 1$ . The pareto-optimal solution of problem (2.9), i.e., subjective preference solution of problem (2.4), can be easily solved by means of simplex method if all the related parameters are given.

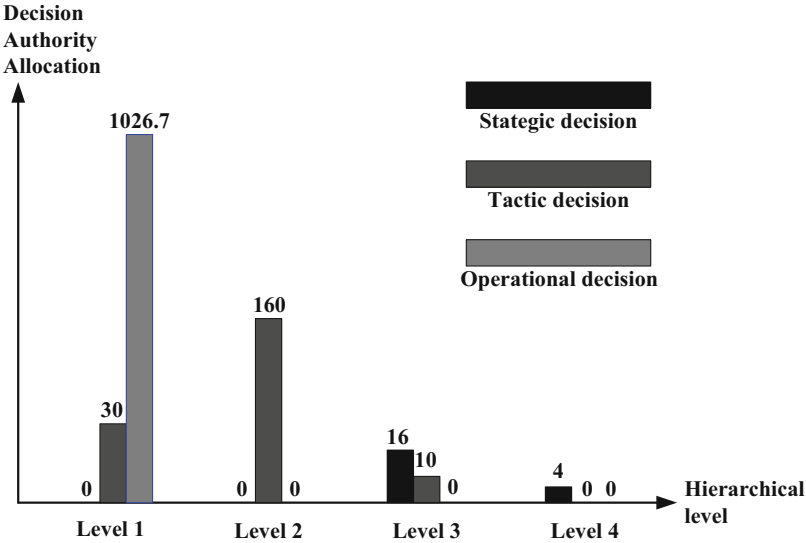
**Proposition 1** *Solve the minimization of the weighted sum function (2.9) and obtain the optimal solution  $\widetilde{k_{ni}}$ . Then  $\widetilde{k_{ni}}$  is also an efficient solution of problem (2.4).*

**Proof** Since  $\widetilde{k_{ni}}$  is the optimal solution of the weighted single-objective problem (2.9), for any  $k_{ni} \in D$ , we have  $w_1 ol(\widetilde{k_{ni}}) - w_2 tb(\widetilde{k_{ni}}) + w_3 dt(\widetilde{k_{ni}}) \leq w_1 ol(k_{ni}) - w_2 tb(k_{ni}) + w_3 dt(k_{ni})$ . Suppose  $\widetilde{k_{ni}}$  is not an efficient solution of problem (2.4), then there exists at least one  $\overline{k_{ni}} \in D$  that satisfies  $OL(\overline{k_{ni}}) \leq OL(\widetilde{k_{ni}})$ ,  $-TB(\overline{k_{ni}}) \leq -TB(\widetilde{k_{ni}})$ ,  $DT(\overline{k_{ni}}) \leq DT(\widetilde{k_{ni}})$ , and at least one strict inequality holds. Since  $w_1, w_2, w_3 > 0$ . It is obvious that  $w_1 OL(\overline{k_{ni}}) - w_2 TB(\overline{k_{ni}}) + w_3 DT(\overline{k_{ni}}) \leq w_1 OL(\widetilde{k_{ni}}) - w_2 TB(\widetilde{k_{ni}}) + w_3 DT(\widetilde{k_{ni}})$ . Take the linear transformation of it and we find the contradiction. Thus Proposition 1 is proved. ■

### 2.3.2 Numerical Study

Now we give the default values of the parameters in this chapter as follows:  $K = 2220$ ,  $K_1 = 20$ ,  $K_2 = 200$ ,  $K_3 = 2000$ ;  $\gamma_1 = 0.9$ ,  $\gamma_2 = 0.2$ ,  $\gamma_3 = 0.05$ ;  $N = 4$ ,  $m = 4$ ;  $f_1(n) = (\frac{n}{N})^2$ ,  $f_2(n) = 1 - \frac{(n - \frac{N}{2})^2}{(\frac{N}{2})^2}$ ,  $f_3(n) = \frac{1}{n^2}$ ;  $p = 0.9$ ,  $s = 1$ ;  $t_1 = 10$ ,  $t_2 = 8$ ,  $t_3 = 6$ ;  $T_1 = 100$ ,  $T_2 = 80$ ,  $T_3 = 60$ ,  $T_4 = 40$ . The given default values of the parameters satisfy the constraints in set  $D$ . We obtain the optimal allocation of decision-making authority as shown in Fig. 2.3.

In Fig. 2.3, the decision authority of strategic items is allocated to top managers of level 3 and level 4. All the strategic decision items are allocated. It is intuitive



**Fig. 2.3** The optimal allocation of decision-making authority

that top managers have more knowledge about strategic items and can definitely make comparatively accurate and high-quality decisions. It should be noted that strategic items are quite important to manufacturing enterprises, accurate decisions on this type items can bring more benefit, and the enterprise will suffer greater opportunity loss if a strategic decision is unallocated or unscheduled, namely, the strategic items should be allocated in high priority. Further, most decision authority of strategic items is allocated to level 3. This can be explained by level 4's limited available time and staffs, although level 4 is more knowledgeable. The decision authority of tactic items is mainly allocated to level 2. Also, in our example, all the tactic decision items are allocated. This is because the enterprise may encounter more market opportunities that need tactic decisions. On the other side, tactic items also bring high payoffs. Since the human resource is mainly distributed in middle level and low level, and middle-level staffs are believed to have more expertise in tactic item, it is obvious that middle-level managers mainly focus on tactic decision items. Finally, staffs from level 1 also participate in the rest tactic items. Although staff from level 1 has little knowledge about tactic items, the tactic items are far more important than operational items. On this account, the decision authority of the rest tactic items is allocated to level 1 in priority. It's worth noting that the operational decision items are only allocated to staffs in level 1. This is because most human resource is distributed in level 1 and thus results in adequate available time for decision. Moreover, staffs in level 1 are regarded as most experienced and knowledgeable in operational items. However, compared to the overall time efficiency, the benefit brought by operational items is negligible.

**Table 2.2** The effects of the waiting time on the optimal allocation of decision-making authority

	$k_{11}^*$	$k_{12}^*$	$k_{13}^*$	$k_{21}^*$	$k_{22}^*$	$k_{23}^*$	$k_{31}^*$	$k_{32}^*$	$k_{33}^*$	$k_{41}^*$	$k_{42}^*$	$k_{43}^*$	$TB^*$	$OL^*$	$DT^*$
$s = 0.5$	0	30	1026.7	0	160	0	16	10	0	4	0	0	85.53	48.67	90
$s = 1$	0	30	1026.7	0	160	0	16	10	0	4	0	0	85.53	48.67	100
$s = 1.5$	0	30	1026.7	0	160	0	16	10	0	4	0	0	85.53	48.67	110
$s = 2$	0	30	1026.7	0	160	0	16	10	0	4	0	0	85.53	48.67	120
$s = 2.5$	0	30	1026.7	0	160	0	16	10	0	4	0	0	85.53	48.67	130

With the optimal scheme of decision authority allocation, the total benefit, potential loss of opportunity, and total decision time can be calculated according to Eqs. 2.1, 2.2, and 2.3 as 85.53, 48.67, and 100, respectively. In the following, we analyze the changing tendency of the optimal allocation scheme and objectives with groups of important parameters, such as the information distortion rate  $p$  and the waiting time of decision information delivery  $s$ , the subjective weights of the multi-objectives, and the total hierarchical levels  $N$  and the average management span  $m$  which reflect the tendency of organizational structure under IoT environment. Finally, we analyze our results and further conclude some managerial and practical significances.

More importantly, the acquisition and delivery of product life cycle information under IoT environment are considered to have three typical characters as discussed in Sect. 1. However, how the related parameters can be affected by the information acquisition and transformation characters remains to be explored, which is further related to the change tendency of allocation of different decision-making authority in each hierarchical level of the IoT-based manufacturing enterprise.

Table 2.2 illustrates the influence of the waiting time  $s$ , i.e., the information delivery time at each hierarchical level, on the optimal allocation of decision-making authority. From Table 2.2, it is intuitive that the waiting time almost has no effect on the optimal allocation scheme. Specifically, the total benefit of the enterprise  $TB$  and the expected loss of market opportunities  $OL$  are independent

from  $s$ , and  $s$  is only a constant term of  $DT = \max_n DT_n = \max_n \frac{\sum_{i=1}^3 k_{ni}(t_i + ns)}{m^{N-n}}$  given the default values. Thus, the optimal allocation scheme is not affected by the waiting time. Note that the increase of  $s$  enlarges the average delivery time of decision information, the maximum decision time under the optimal allocation scheme increases with  $s$ . In fact,  $s$  reflects the efficiency of information delivery in each hierarchical level and executive capacity of the staffs, which cannot be simply improved under the environment of information technology.

The optimal allocation scheme of decision-making authority and the corresponding values of enterprise's objectives are shown in Table 2.3 when the distortion rate of information delivery  $p$  changes. From Table 2.3, we can see that higher levels will be allocated less decision items when the distortion rate decreases. This is because the accuracy of decision information made by staffs in

**Table 2.3** The effects of the distortion rate on the optimal allocation of decision-making authority

$p$	$k_{11}^*$	$k_{12}^*$	$k_{13}^*$	$k_{21}^*$	$k_{22}^*$	$k_{23}^*$	$k_{31}^*$	$k_{32}^*$	$k_{33}^*$	$k_{41}^*$	$k_{42}^*$	$k_{43}^*$	$TB^*$	$OL^*$	$DT^*$
0.9	0	30	1026.7	0	160	0	16	10	0	4	0	0	85.53	48.67	100
0.8	0	30	1026.7	0	160	0	16	10	0	4	0	0	71.54	48.67	100
0.7	0	40	1013.3	0	160	0	16	0	13.3	4	0	0	59.01	48.67	100
0.6	0	40	1013.3	0	160	0	16	0	13.3	4	0	0	47.75	48.67	100
0.5	0	30	1026.7	0	160	0	20	0	6.7	0	0	6.7	37.60	48.67	100

**Table 2.4** The effects of the objective weights on the optimal allocation of decision-making authority

$w$	$k_{11}^*$	$k_{12}^*$	$k_{13}^*$	$k_{21}^*$	$k_{22}^*$	$k_{23}^*$	$k_{31}^*$	$k_{32}^*$	$k_{33}^*$	$k_{41}^*$	$k_{42}^*$	$k_{43}^*$	$TB^*$	$OL^*$	$DT^*$
$(\frac{1}{3}, \frac{1}{3}, \frac{1}{3})$	0	30	1026.7	0	160	0	16	10	0	4	0	0	85.53	48.67	100
$(\frac{1}{2}, \frac{1}{4}, \frac{1}{4})$	0	30	1026.7	0	160	0	16	10	0	4	0	0	85.53	48.67	100
$(\frac{1}{2}, \frac{1}{2}, \frac{1}{4})$	0	30	1026.7	0	160	0	16	10	0	4	0	0	85.53	48.67	100
$(\frac{1}{4}, \frac{1}{4}, \frac{1}{2})$	0	62.8	646.1	0	127.2	0	16	10	0	4	0	0	67.52	67.69	79.5

higher level decreases sharply with a very low information distortion rate. It should be pointed that when  $p$  decreases, the decision authority of items with higher importance will be gradually allocated to lower hierarchical levels, even though staffs in higher level have more knowledge on these items. Since the distortion rate  $p$  is only related to the objective of enterprise's total benefit, the objectives of potential opportunity losses and the maximum average decision time are not affected by  $p$ . Moreover, the distortion rate  $p$  under IoT environment is significantly larger than traditional manufacturing scenarios according to the information acquisition and transformation characteristics. In this way, the decision authority of important decision items is more likely to be allocated to higher levels due to their abundant knowledge and the high information distortion rate, thus generating more total benefits.

Table 2.4 indicates the effects of subjective weights of enterprise's objective functions on the optimal allocation scheme of decision authority. In our example, there is a big difference between  $\gamma_i$ , the importance of different types of decision items. When the objective of total benefit maximization is given a large weight, the higher hierarchical level should be allocated the decision authority of items with higher importance considering the high distortion rate under the constraint of available time. Thus, the optimal allocation scheme remains unchanged. Similarly, when the objective of potential opportunity loss minimization is given a large weight, considering the far low importance of the operational decision items, the items of high importance should be allocated to higher level in priority. However, when the maximal decision time is given a large weight, the total expected benefit and potential opportunity loss will be less important. In this way, it is optimal to allocate the decision authority of less decision items with the purpose of saving total decision time, which leads to less total benefit and more expected opportunity losses.



The optimal organizational structure of the enterprises is always changing due to dynamic market and improvement in information technology. In order to accelerate the information delivery and reduce distortion of decision information result in redundant middle levels, enterprises need to reduce the decision levels accordingly. However, the reduction of decision levels implies more potential opportunity losses. It is significant and interesting to analyze the optimal hierarchy of enterprises and its changing tendency based on the three characteristics under the IoT environment. From Eqs. 2.1, 2.2, and 2.3, it is difficult to judge how the enterprise's objectives will be changing with the hierarchical level and the management span. In our example, when the organizational designer chooses to reduce the hierarchical level to  $N=3$ , then we have the management span  $m=8.68$ , that is, no staffs are dismissed or newly recruited. Also, when the hierarchical level is increased to  $N=5$ , we have  $m=2.71$ . We conclude the optimal allocation of decision-making authority in Table 2.5. We use the same default values of the parameters. In addition, we define  $T_5=20$ .

It is obvious that the decrease of the hierarchical level will significantly increase the management span of the organization. In our numerical example, the decision-making authority of strategic items is always mostly allocated to higher levels and operational items allocated to the lower levels. However, when there are less hierarchical levels, the division of responsibilities is much clearer. This helps different layers to concentrate on less types of decision items. Our results show that when the hierarchical level increases, staffs in the higher level will have less available time for decision making. The higher level will be allocated less decision authority of items, especially items with high importance. Other than the available time, the high delivery distortion of decision information due to more interlayers is another factor that influences the enterprise's expected total benefit. It should be noted that there will be less staffs in each level when  $N$  is larger; thus less decision authority of items will be allocated to each level when  $N$  increases.

Furthermore, Table 2.5 shows that enterprise's expected total benefit decreases with  $N$ . A possible explanation is the high distortion rate of decision information that makes a low accuracy of decision information. In addition, the increase of hierarchical levels implies more losses of market opportunities. In this way, the organizational structure with more levels operates inefficiently since the management span is too small. More time are wasted in the information delivery between interlayers. Under the intelligent manufacturing environment based on the Internet of Things, the information is more accurately delivered to the bottom level for implementation due to a larger information distortion rate. Based on the analysis of Table 2.5, it is suggested that the organizational designer should reduce the hierarchical levels to make an efficient and flat organizational structure.

**Table 2.5**    The effects of hierarchical level on the optimal allocation of decision-making authority

$N$	$k_{11}^*$	$k_{12}^*$	$k_{13}^*$	$k_{21}^*$	$k_{22}^*$	$k_{23}^*$	$k_{31}^*$	$k_{32}^*$	$k_{33}^*$	$k_{41}^*$	$k_{42}^*$	$k_{43}^*$	$k_{51}^*$	$k_{52}^*$	$k_{53}^*$	$TB^*$	$OL^*$	$DT^*$
3	0	130.7	1081.4	14	69.3	0	6	0	0	—	—	—	—	—	—	88.03	45.93	99.19
4	0	30	1026.7	0	160	0	16	10	0	4	0	0	—	—	—	85.53	48.67	100
5	0	0	898.93	0	199	0	7.16	0.97	60.21	10.84	0	0	2	0	0	78.25	52.04	100

2.4 Sequential Game Model for Centralization Behavior

In this section, a sequential game model is proposed to analyze the centralization behavior of each hierarchy from a microcosmic perspective. We solve the optimal centralization behavior of each hierarchical level toward different types of items through a multivariate layer optimization model. Some suggestions are finally proposed to adjust incentive mechanism which guides staffs to behave closely to the optimal allocation scheme of decision-making authority. Our effort creatively quantifies enterprise’s decision authorities, which also has great practical significance for IoT-based manufacturing enterprises to adjust the organizational structure and design incentive mechanisms.

2.4.1 The Sequential Game Model

Although the optimal allocation of the decision-making authority is solved by minimizing the average decision time and opportunity losses and maximizing firm’s total benefits, the full implementation of this scheme can be difficult. In fact, each hierarchical level will also balance the benefits and contributions from its own perspective to choose an optimal rate for centralization or decentralization. In this way, enterprise’s optimal allocation of decision authority can be meaningless for practice. In this section, we consider the centralization mechanism of different levels from microcosmic perspective using sequential game theory to study how enterprise’s optimal allocation scheme can be implemented. Furthermore, an incentive mechanism is designed for levels to choose the centralization rate that is close to enterprise’s optimal allocation scheme.

Figure 2.4 illustrates the structure of the sequential game which describes the decision process of level’s centralization or decentralization. With regard to each type of decision item, each level  $n$  can choose to implement the decision authority with the limitation of its available time or delegate the decision authority to lower

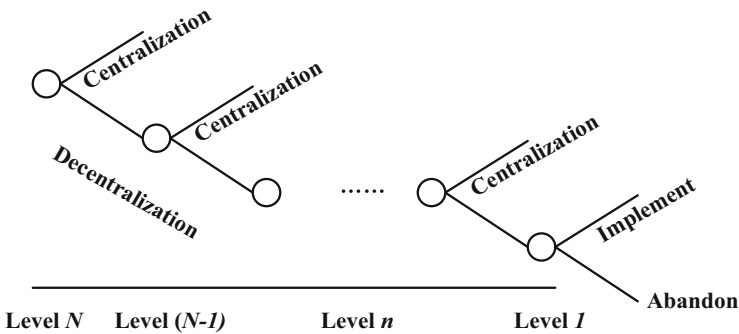


Fig. 2.4 Structure of the sequential game

level. However, when the decision authorities of different items are decentralized to the bottom level 1, it only has two choices including implementing the decision items and abandoning them.

Let  $x_{ni}$  be the decentralization probability of level  $n$  toward items of type  $i$ , where  $x_{ni} \in [0, 1]$ ,  $n \in \{1, 2, \dots, N\}$ , and  $i \in \{1, 2, 3\}$ . Then its centralization probability is  $(1 - x_{ni})$ .  $AC_{ni}$  denotes level  $n$ 's expected benefit oriented from decision item of  $i$  type when it chooses the centralization behavior, and  $AD_{ni}$  represents its expected benefit oriented from  $i$  type decision item when it chooses the decentralization behavior. Each level will benefit  $B_i$  when an  $i$  type decision item is accurately decided and implemented. In addition, level  $n$  will generate a unit decision cost  $C_i$  if it chooses the centralization behavior. This can be explained as labor cost, time cost, and so on. To encourage the centralization behavior, level  $n$  is rewarded a bonus  $M_{ni}$  if it chooses the centralization behavior and the decision is accurately made, delivered, and implemented. We conclude the notations used in this section in Table 2.6 as follows. Other used notations can be found in Table 2.1.

Firstly, level  $n$  will not always have the opportunity to decide its behavior of centralization or decentralization. When and only when all the higher levels of level  $n$  choose the decentralization decision can level  $n$  have the opportunity. When level  $j$  ( $j > n$ ) takes the decision authority of an  $i$  type item, level  $n$ 's expected benefit oriented from an  $i$  type item can be derived as

$$RA_{ni} = B_i \sum_{j=n+1}^N f_i(j) p^j \left[ x_{ji} \prod_{k=j+1}^N (1 - x_{ki}) \right] \quad (2.10)$$

We explain Eq. 2.10 as follows: when the decision is made in level  $j$  ( $j \in \{n+1, n+2, \dots, N\}$ ), level  $n$  will also get a benefit of  $B_i$  if the item is accurately decided

and implemented.  $x_{ji} \prod_{k=j+1}^N (1 - x_{ki})$  denotes the probability that the decision

**Table 2.6** Notations of the sequential game model

Notation	Description
$x_{ni}$	Level $n$ 's centralization probability toward $i$ type items, $x_{ni} \in [0, 1]$
$B_i$	Each level's benefit if an $i$ type item is perfectly implemented
$C_i$	Unit decision cost of an $i$ type item
$M_{ni}$	Level $n$ 's unit bonus if its decision on an $i$ type item is perfectly implemented
$RA_{ni}$	Level $n$ 's expected benefit oriented from an $i$ type decision item when the authority is taken by levels higher than $n$
$AC_{ni}$	Level $n$ 's expected benefit oriented from an $i$ type decision item when level $n$ chooses the centralization behavior
$AD_{ni}$	Level $n$ 's expected benefit oriented from an $i$ type decision item when the authority is taken by levels lower than $n$
$A_{ni}$	Level $n$ 's expected benefit oriented from an $i$ type decision item
$TA_n$	Average total benefit of level $n$ oriented from all decision items

authority of the  $i$  type level is taken in a level higher than  $n$ .  $f_i(j)$  represents the knowledge of level  $j$  on  $i$  type decision item, which can also be understood as the decision accuracy.  $p^j$  denotes the distortion rate of decision information when it is delivered from level  $j$  to level 0. Thus, when level  $j$  chooses the centralization behavior and takes the decision authority of an  $i$  type item, the accuracy of implementation is  $f_i(j)p^j$ . Thus Eq. 2.10 is derived.

When level  $n$  has the choice of centralization and decentralization behaviors, it also implies that the decision authority of a  $i$  level item is given up by levels higher than  $n$  simultaneously. We derive the expected benefit oriented from an  $i$  type decision item when it chooses the centralization behavior as follows:

$$AC_{ni} = (B_i + M_{ni} - C_i) \left[ \sum_{j=n+1}^N (1 - x_{ji}) \right] x_{ni} f_i(n) p^n \quad (2.11)$$

In Eq. 2.11,  $\sum_{j=n+1}^N (1 - x_{ji}) x_{ni}$  denotes the probability that levels higher than  $n$  take the decentralization decision simultaneously.  $f_i(n)$  represents the knowledge of level  $n$  on  $i$  type decision item, which can also be understood as the decision accuracy.  $p^n$  denotes the distortion rate of decision information when it is delivered from level  $n$  to level 0. Thus when level  $n$  chooses the centralization behavior and takes the decision authority of an  $i$  type item, the implementation accuracy is  $f_i(n)p^n$ . In addition, when an  $i$  type item is accurately implemented, the expected benefit is  $(B_i + M_{ni} - C_i)$ .

Also, when level  $n$  chooses the decentralization behavior and delegates the decision authority of an  $i$  type item to lower level, the expected benefit can then be derived as

$$AD_{ni} = B_i \left[ \sum_{j=n}^N (1 - x_{ji}) \right] \sum_{u=1}^{n-1} f_i(u) p^u \left[ x_u \prod_{v=u+1}^{n-1} (1 - x_v) \right] \quad (2.12)$$

In Eq. 2.12,  $\sum_{j=n}^N (1 - x_{ji})$  means that all the levels higher than  $n$  (included) choose the decentralization behavior.  $x_u \prod_{v=u+1}^{n-1} (1 - x_v)$  further represents the probability that the decision authority is allocated to level  $u$ , ( $u \in \{1, 2, \dots, n-1\}$ ). When the decision authority of an  $i$  type decision item is taken by level  $u$ , and the decision information is delivered and implemented in level 0, the implementation accuracy is  $f_i(u)p^u$ . In addition, level  $n$  will receive a benefit  $B_i$  no matter in which level the authority of an  $i$  type item is accurately taken and implemented.

Based on Eq. 2.10, 2.11, and 2.12, we derive the expected unit benefit  $A_{ni}$  of level  $n$  oriented from an  $i$  type item as follows:

$$\begin{aligned}
A_{ni} &= RA_{ni} + AC_{ni} + AD_{ni} \\
&= B_i \sum_{j=n+1}^N f_i(j) p^j \left[ x_{ji} \prod_{k=j+1}^N (1 - x_{ki}) \right] \\
&\quad + (B_i + M_{ni} - C_i) \left[ \sum_{j=n+1}^N (1 - x_{ji}) \right] x_{ni} f_i(n) p^n \\
&\quad + B_i \left[ \sum_{j=n}^N (1 - x_{ji}) \right] \sum_{u=1}^{n-1} f_i(u) p^u \left[ x_{ui} \prod_{v=u+1}^{n-1} (1 - x_v) \right] \tag{2.12}
\end{aligned}$$

As we have derived the expected unit benefit  $A_{ni}$  of level  $n$  oriented from an  $i$  type item when it is decided at any level, however, note that the enterprise will encounter  $K_i$  items of  $i$  type and each level has  $m^{(N-n)}$  staffs. We derive the average total benefit of a staff in level  $n$  as

$$TA_n = \frac{1}{m^{(N-n)}} \sum_{i=1}^3 K_i A_{ni} \tag{2.13}$$

In Eq. 2.13,  $\sum_{i=1}^3 K_i A_{ni}$  represents the total benefits that level  $n$  gets from the  $K_i i$  type decision items ( $i = 1, 2, 3$ ). In fact,  $TA_n$  is the average total benefit of level  $n$  oriented from all decision items. Since  $TA_n$  reflects the total benefits that each staff in level  $n$  can get, it is also important that each staff will choose its own preferences/probabilities of centralization toward each type of decision item  $x_{ni}$  to maximize  $TA_n$ .

It is worth noting that the preferences of level  $n$ 's centralization are restrained by its available time. Since the probability that level  $n$  takes the decision authority of an  $i$  type decision item is  $x_{ni} \prod_{j=n+1}^N (1 - x_{ji})$ , the total time that level  $n$  spends on all decision items is  $\sum_{i=1}^3 \left[ K_i t_i x_{ni} \prod_{j=n+1}^N (1 - x_{ji}) \right]$ . Thus the restraints of available time can be derived as follows:

$$\frac{1}{m^{(N-n)}} \sum_{i=1}^3 \left[ K_i t_i x_{ni} \prod_{j=n+1}^N (1 - x_{ji}) \right] \leq T_n \tag{2.14}$$

Note that the sum of each type of decision items should not exceed the total numbers of decision item that the enterprise encounters. Since the centralization probability of level  $n$  toward items of  $i$  type is  $x_{ni}$ , it is obvious that the number of  $i$  type items that staffs in level  $n$  will take the decision-making authority is  $K_i x_{ni} \prod_{j=n+1}^N (1 - x_{ji})$ . Thus, we have  $\sum_{n=1}^N K_i x_{ni} \prod_{j=n+1}^N (1 - x_{ji}) \leq K_i$ . In other words, we have

$$\sum_{n=1}^N x_{ni} \prod_{j=n+1}^N (1 - x_{ji}) \leq 1 \quad (2.15)$$

From Eqs. 2.13, 2.14, and 2.15, our problem can eventually be induced into a multi-objective (or can be regarded as single-objective) and multivariate optimization problem as follows:

$$\max TA_n = \frac{1}{m^{(N-n)}} \sum_{i=1}^3 K_i A_{ni} \quad (2.16)$$

$$s.t. \quad \frac{1}{m^{(N-n)}} \sum_{i=1}^3 \left[ K_i t_i x_{ni} \prod_{j=n+1}^N (1 - x_{ji}) \right] \leq T_n$$

$$\sum_{n=1}^N x_{ni} \prod_{j=n+1}^N (1 - x_{ji}) \leq 1$$

$$x_{ni} \in [0, 1]$$

$$\text{where } A_{ni} = B_i \sum_{j=n+1}^N f_i(j) p^j \left[ x_{ji} \prod_{k=j+1}^N (1 - x_{ki}) \right] + (B_i + M_{ni} - C_i) \left[ \sum_{j=n+1}^N (1 - x_{ji}) \right] \\ x_{ni} f_i(n) p^n + B_i \left[ \sum_{j=n}^N (1 - x_{ji}) \right] \sum_{u=1}^{n-1} f_i(u) p^u \left[ x_u \prod_{v=u+1}^{n-1} (1 - x_v) \right].$$

**Proposition 2** *The staff in level n is more likely to choose centralization behavior toward a type i decision item when the difference between the bonus given by the enterprise and the decision cost  $M_{ni} - C_i \geq B_i$*

$$\left( \frac{\left[ \sum_{j=n}^N (1 - x_{ji}) \right] \sum_{u=1}^{n-1} f_i(u) p^u \left[ x_u \prod_{v=u+1}^{n-1} (1 - x_v) \right]}{\left[ \sum_{j=n+1}^N (1 - x_{ji}) \right] x_{ni} f_i(n) p^n} - 1 \right).$$

**Proof** When level  $n$  has the opportunity to choose the centralization or decentralization behavior toward a type  $i$  item, it is obvious that the decision-making authority of the item is delegated by levels higher than  $n$ . Thus, the staff in level  $n$  will make a decision that maximizes the expected benefit. When  $AC_{ni} > AD_{ni}$ , it is better to keep the decision-making authority and make a centralization behavior.

$$\text{Substitute} \quad AC_{ni} = (B_i + M_{ni} - C_i) \left[ \sum_{j=n+1}^N (1 - x_{ji}) \right] x_{ni} f_i(n) p^n \quad \text{and}$$

$$AD_{ni} = B_i \left[ \sum_{j=n}^N (1 - x_{ji}) \right] \sum_{u=1}^{n-1} f_i(u) p^u \left[ x_u \prod_{v=u+1}^{n-1} (1 - x_v) \right], \quad \text{and simplify the}$$

inequation, and Proposition 2 is proved. ■

Proposition 2 gives the relationship between the enterprise's incentive bonus and the decision cost. Given the decision cost and the optimal probabilities of level  $n$ 's centralization behavior  $n \in \{1, 2, \dots, N\}$ , the organization designer can then make an incentive bonus for staffs to guide their behavior according to the optimal allocation scheme of decision-making authorities.

**Proposition 3** *If level  $n$  has enough available decision time and is required to make a choice of centralization or decentralization behavior toward  $i$  type items and  $j$  type items, where  $i \neq j$  and  $i, j \in \{1, 2, 3\}$ , then the staff in level  $n$  will keep the decision-making authority of  $i$  type items in priority if and only if*

$$\frac{B_i + M_{ni} - C_i}{B_j + M_{nj} - C_j} \geq \frac{t_i f_j(n)}{t_j f_i(n)}.$$

**Proof** In fact, when a staff in level  $n$  is confronted with the choice of centralization behavior between  $i$  type items and  $j$  type items, the only judgment is to generate more benefit within the same decision time. If the staff chooses the  $i$  type items, then the profit is  $(B_i + M_{ni} - C_i)f_i(n)p^n$ , and the decision time of an  $i$  type item is  $t_i$ . Thus, the profit generated per time unit can be derived as  $\frac{(B_i + M_{ni} - C_i)f_i(n)p^n}{t_i}$ . The profit

generated per time unit of the  $j$  type item can then be derived as  $\frac{(B_j + M_{nj} - C_j)f_j(n)p^n}{t_j}$

similarly. Therefore, when  $\frac{(B_i + M_{ni} - C_i)f_i(n)p^n}{t_i} > \frac{(B_j + M_{nj} - C_j)f_j(n)p^n}{t_j}$ , i.e.,  $\frac{B_i + M_{ni} - C_i}{B_j + M_{nj} - C_j} \geq$

$\frac{t_i f_j(n)}{t_j f_i(n)}$ , a staff in level  $n$  will keep the decision authority of  $i$  type items in priority. ■

From Proposition 3, we can further propose that when the staffs in hierarchical level  $n$  are confronted by multiple types of decision items within their available time, they will definitely choose to keep the decision authority of the type which can generate the largest profit per decision time unit. When staffs in level  $n$  take all the decision authority of this type of decision item and they still have available decision time, they will then choose to keep the decision authority of the type of item which can generate the second largest profit per decision time unit, by that analogy until no available decision time left. From Proposition 3, on the other hand, the organization designer can also make an incentive scheme that leads to the optimal allocation of decision authority that maximizes enterprise's multi-objectives.

## 2.4.2 Numerical Study

In problem (2.16), we should solve the optimal probabilities of centralization of level  $n$  toward decision item  $i$ , where  $n = \{1, 2, \dots, N\}$  and  $i = 1, 2, 3$ , to maximize the total profit of each staff in level  $n$  under the restraints of available time. To solve the exact analytical solution of problem (2.16) can be extremely difficult and complex. Similarly, we also try to solve the optimal numerical solution given default values of related parameters in Sect. 3. In addition, the default value  $B =$



$[3, 1, 0.2]$ ,  $C = [3, 2, 1]$ . Moreover, we define that  $M_{ni} = 9$ ,  $M_{ni} = 5$ , and  $M_{ni} = 2$ . This means that the organization designer will make no difference on which level takes the decision authority of the  $i$  type decision items.

In fact, problem (2.16) is a sequential game theoretic model that higher level can make a decision of its own centralization probability to maximize its own expected total profit. It should be noted that there can be free-riding behavior. For example, sometimes a specific layer will benefit more if he delegates the decision authority to lower layer since the higher layer has little knowledge on the decision items. Moreover, it is a waste of available time that should be spent on the items that it has more knowledge. By solving the multivariate layer planning model of problem (2.16), we get the optimal centralization probabilities of each level toward different types of decision items as follows:

$$x_{ni}^* = \begin{bmatrix} x_{11}^* & x_{12}^* & x_{13}^* \\ x_{21}^* & x_{22}^* & x_{23}^* \\ x_{31}^* & x_{32}^* & x_{33}^* \\ x_{41}^* & x_{42}^* & x_{43}^* \end{bmatrix} = \begin{bmatrix} 0 & 1 & 0.51 \\ 1 & 0.69 & 0.02 \\ 0.86 & 0.11 & 0 \\ 0.2 & 0 & 0 \end{bmatrix}$$

From the levels' subjective centralization probabilities toward different types of decision items, we can see that the highest level will keep the decision authority of the strategic decision items at the restriction of its available time. In our example, this is mainly because the highest level has the most knowledge on the strategic items, making the items more accurately implemented, despite the lower distortion rate. Also, when a strategic decision item is accurately implemented, the layer will be awarded a high bonus. At the third level, however, the knowledge on strategic decision items decreases, while its knowledge on the tactic increases. Thus, it will keep the decision authority of more tactic items. Specifically, the lowest level has the most knowledge on operational items. However, the profit brought by the operational decision is comparatively low. Considering its limited available decision time, it should choose the tactic decision items in priority.

To regulate the centralization behavior of different levels with the purpose of maximizing enterprise's multi-objectives, we first deduce the optimal centralization probabilities of each level toward different items according to Fig. 2.3 as follows:

$$\tilde{x}_{ni}^* = \begin{bmatrix} \tilde{x}_{11}^* & \tilde{x}_{12}^* & \tilde{x}_{13}^* \\ \tilde{x}_{21}^* & \tilde{x}_{22}^* & \tilde{x}_{23}^* \\ \tilde{x}_{31}^* & \tilde{x}_{32}^* & \tilde{x}_{33}^* \\ \tilde{x}_{41}^* & \tilde{x}_{42}^* & \tilde{x}_{43}^* \end{bmatrix} = \begin{bmatrix} 0 & 1 & 0.51 \\ 0 & 0.84 & 0 \\ 1 & 0.05 & 0 \\ 0.2 & 0 & 0 \end{bmatrix}$$

In fact, there is minor difference between  $x_{ni}^*$  and  $\tilde{x}_{ni}^*$  that the highest level still only keeps the decision authority of strategic items. No significant conflicts exist

between the enterprise's benefit and the highest level's benefit in the centralization behavior toward strategic items. From Proposition 3, the lowest level will choose to keep the decision authority of tactic items in priority for the larger  $\frac{B_2+M_{12}-C_2}{t_2}pf_2(1)$ , the profit brought by tactical items per time unit. The most difference is that the interlayers hesitate in concentrating more in strategic items or tactic items for they have high knowledge on both types of items. The organizational designer should make an efficient incentive bonus of  $M_{ni}$  with the purpose of guiding different layers to behave in preferences that are most close to the optimal allocations of the enterprise's decision items. Let the  $x_{ni}$  in problem (2.16) be known variables as given  $\tilde{x}_{ni}^*$ , and solve the multivariate layer planning model, and we have

$$M_{ni}^* = \begin{bmatrix} 0 & 2 & 0.8 \\ 0 & 6.74 & 0 \\ 10.31 & 3.87 & 0 \\ 9 & 0 & 0 \end{bmatrix}$$

$M_{ni}^*$  is the minimum incentive bonus that the organization designer needs to pay for staffs in different levels toward different decision items. However, there will be multiple feasible solutions. In our example,  $M_{ni}^*$  shows that the organizational designer should make a scheme of incentive bonus considering the benefit of different layers. For example, to encourage the centralization behavior of level 2 toward tactic items, the incentive bonus should be specifically increased. However, to encourage the decentralization behavior of level 3 toward tactic items, both the incentive bonus of the level toward strategic and tactic items should be adjusted accordingly.

## 2.5 Conclusion and Further Research

### 2.5.1 Conclusion

The emerging information technologies of the IoT and big data have changed customers' personalized demands and accelerated the information transformation between and inside enterprises. Also, traditional production patterns of manufacturing enterprises have changed. According to the previous literature, we conclude that there are three advantages of information acquisition and delivery in IoT manufacturing enterprises compared to that of traditional manufacturing scenarios: (1) more comprehensive acquisition of product life cycle information, (2) precise detection and analysis of on-site data, and (3) faster information transmission inside and among cooperative enterprises.

Despite the technical convenience and advantages that the IoT brought to the manufacturing process, this chapter mainly concentrates on the optimal allocation

of decision-making authority of strategic, tactic, and operational decision items with the objectives of maximization of total profit and minimization of expected opportunity losses and maximal decision time. After we solve the optimal allocation scheme of decision-making authority, we explore the centralization behavior of different layers from a microcosmic perspective. The problems are analyzed and solved in an established multi-objective optimization model and a multivariate layer planning model, respectively. Due to the complexity of analytical solution, our results are solved and tested in a numerical example. Finally, we propose suggestions for change of organizational structure and incentive mechanism for organization planner.

We find that the optimal allocation of decision-making authority toward different types of decision items is significantly affected by the distortion rate of decision information delivery, while independent from the waiting time of information delivery in interlayers and enterprise's preference of the objectives. Most importantly, the hierarchical levels under IoT environment are suggested to be reduced to make an efficient and flat organizational structure. Then, we propose that the knowledge functions, incentive mechanism, decision costs, and the decision time have synthetic influences on the centralization behavior of different levels toward decision items.

### ***2.5.2 Future Research***

Our work creatively introduces methods to quantify the decision authority and the decision information transformation and solve the optimal allocation scheme under the restrictions of enterprise's resources. Our work contributes for the new directions to look into the governance of internal organizational structure, which is also significantly effective to propose directions for the allocation of decision authority and organizational change under IoT environment. However, our results are mostly analyzed from a numerical example due to the complexity of solving analytical solutions of the multi-objective optimization mode. Further study could consider the optimal hierarchical level and management span according to the characteristics of information acquisition and delivery under intelligent manufacturing environment. Moreover, how can the decision efficiency of an IoT-based manufacturing enterprise be improved can be interesting and meaningful.

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