INTERNATIONAL JOURNAL OF COMPUTERS COMMUNICATIONS & CONTROL
ISSN 1841-9836, 13(5), 895-907, October 2018.

Service Innovation Decision Analysis Based on Influence Diagrams

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Abstract: The influence diagram is a probabilistic model for presenting decision problems as a directed graph. In this study, the dynamic influence diagram and the interactive dynamic influence diagram are used to model the three parties to service innovation: customers, suppliers, and service enterprises. The models analyze the decisions of these different parties and describe the process by which service enterprises should consider their own innovation conditions as well as those of the other parties, that is, customers and suppliers. Moreover, during the process of service innovation, service enterprises should be in constant communication with customers and suppliers. After the customers and suppliers respond, service enterprises can modify their innovation decision-making, and improve service innovation quality and income.
Keywords: influence diagram, service innovation, decision-making.

1 Introduction

Traditional decision-making tools such as the decision tree and decision table are limited and cannot describe the conditional independence and time sequence relations between uncertain quantities. By contrast, the influence diagram (ID)- a probabilistic model for presenting decision problems as a directed graph-uses these relations to simplify the solution, thereby quickly becoming a research hotspot and the key point of decision analysis in uncertain environments. Koller in Stanford University et al. propose a multi-agent ID (MAID), which uses a structure that affects the characteristics of the game, combined with game theory and the graph model [12]. MAID can effectively represent the static structure between the multi-agent relationship, and deal with complex multi-agent countermeasures. Compared with game theory, MAID increases the conditional independence of uncertain variables, thereby simplifying the model and making it easier to solve. In order to express the temporal relation, this paper applies dynamic ID (DID) or interactive DID (I-DID) to solve dynamic decision-making problems with single or multiple agents [14].

Service innovation refers to new ideas, new technical methods, and new or improved service, to ensure that potential users have a service experience that is different from past experiences [4]. Service innovation is not restricted to service industry innovation alone; all service-related innovations can be classified under the concept of service innovation [17]. Bilderbeek, Hertog et al. developed the four-dimension model of service innovation, consisting of new service concepts, service delivery systems, customer interfaces, and non-technical factors [3]. Hertog classified the innovation of service enterprises into five modes-internal innovation, service process innovation, comprehensive innovation, customer-driven innovation, and supplier-dominated innovation and discussed the positive effect of knowledge-intensive services on the role of innovation. Aranda, Molina–Fernández, who created the service innovation degree model, emphasized that organization members' knowledge and their ability to exchange such knowledge effectively, is the foundation of successful innovation. Therefore, knowledge management has become a decisive factor in service innovation [2]. Galluj believes that service innovation has two main interaction features: (1) external interaction, which refers to employees interacting with external customers and (2) internal interaction, which refers to the interaction between internal staff and the senior leadership. The two parties will consciously or subconsciously participate in driving innovation consciousness [9].

2 Participants in service innovation

Service innovation mainly consists of three participants-service enterprises, customers, and suppliers. Enterprise leaders, top-level staff members, and innovation teams together implement service innovation through the internal structure of the enterprise. The participation of customers and suppliers in service innovation is an important channel for innovation and supports service innovation through the external structure of the service enterprise. As is shown in Figure 1, service innovation is a process in which managers, employees, innovation teams, customers, and suppliers jointly participate.

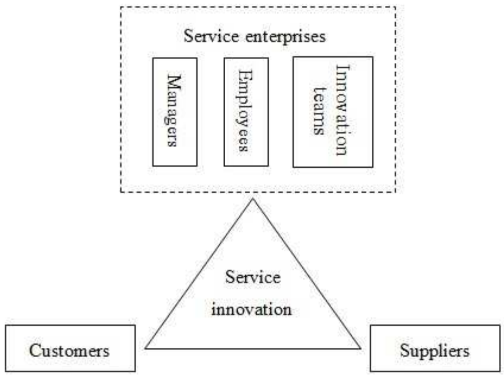

Figure 1: Participants in Service Innovation

Service innovation is often created through the cooperation of service enterprises, customers, and suppliers. The overall process of service innovation refers to participation in the transformation of ability from an internal point of view. When defining innovation, service enterprises, customers (existing customers, planned customers, potential customers), and suppliers often convey their opinions to the senior staff, leaders, and innovation groups of service companies. They cooperate with the company to implement innovative ideas more effectively and facilitate the emergence of new service definitions. Service enterprises need customers and suppliers to participate in the research and development (R&D) and planning of new services. This cooperative process allows each participant to shares their ability. After new service plans are developed, it is necessary to implement these plans. All staff, right from the top to the bottom, need to learn the new service concepts to facilitate new service delivery, marketing management, sales service, and so on. In the process of following reviews and innovation safeguards, the content transformation between companies and their customers is critical. The service company may obtain market evaluations of the new service from customers and implement the relevant innovation guarantee scheme in the new service, which cannot spread the knowledge between the customer and the company. Therefore, service innovation is a comprehensive process that involves many important participants. There are three main aspects to service innovation: (1) knowledge transfer from customers; (2) knowledge integration of service enterprises; and (3) knowledge sharing of suppliers.

In general, service innovation is an activity that many subjects participate in together. The service enterprise designs and develops the innovation. The customer is the motivation behind the innovation and accepts the results. The supplier is a partner in service innovation [20,21]. In this process, customers, suppliers, and service enterprises are all agents. The three-party decision-making system is, thus, a multi-agent decision making model. There is considerable literature that uses game and evolution game theory to analyze the decision-making relationship. So, I-DID is used to analyze the evolutionary relationship among the three parties [13], and the simplified Discriminative Model Updates (DMU) model is used to solve the decision problems of service innovation [18].

3 ID of single agent

First, the customer ID is modeled as shown in Figure 2. Suppose the customer is agent j; the customer's possible actions are participation and non-participation; the possible observation values are that the innovation conditions are mature or that they are immature.

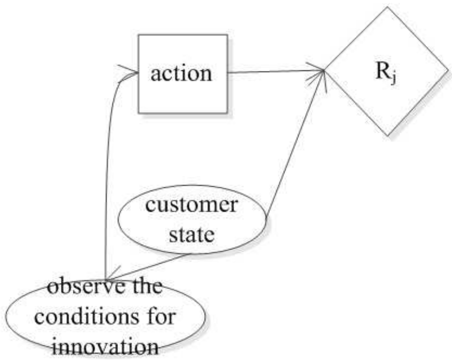

Figure 2: A Customer ID Model

In the figure, the rectangle is the decision node; the state and observation are random nodes, represented by an ellipse and associated with a conditional probability table; R_j is the value node, represented by a rhombus and associated with a value function. Suppose that the probability of customers' interest is x_1. The conditional probability of the state transfer function of the customer is shown in Table 1, the conditional probability of the observation function is shown in Table 2, and the conditional probability of the value function is shown in Table 3.

Table 1: Conditional Probability of Customers' State Transfer Function

Interested	Disinterested
x_1	$1-x_1$

Secondly, the supplier's ID is modeled as shown in Figure 3. Suppose the supplier is agent k; the supplier's possible actions are cooperation and non-cooperation; the possible observations are that the conditions of innovation are mature or that they are immature.

Suppose that the probability of the supplier's interest is x_2. The conditional probability of the state transfer function of the supplier is shown in Table 4, the conditional probability of the

Table 2: Conditional Probability of Customers' Observation Function

State	Mature Innovation Conditions	Immature Innovation Conditions
Interested	y_1	1-y_1
Disinterested	1-y_1	y_1

Table 3: Conditional Probability of Customers' Value Function

Action	Interested	Disinterested
Participation	z_{11}	z_{12}
Non-Participation	z_{13}	z_{14}

observation function is shown in Table 5, and the conditional probability of the value function is shown in Table 6.

Finally, the ID model of the service enterprise is as shown in Figure 4. Suppose that the service enterprise is the deciding agent i. There are two possible actions-innovation, non-innovation; the possible observations are that the conditions of innovation are mature or that they are immature; moreover, there are two states of service enterprises-interested and disinterested.

Suppose that the probability of service enterprise interest is x_3. The conditional probability of the state transfer function of the supplier is shown in Table 7, the conditional probability of the observation function is shown in Table 8, and the conditional probability of the value function is shown in Table 9.

4 ID of multiple agents

In order to research the multi-agent decision-making problem in a dynamic uncertain environment, MAID, interactive ID, and I-DID are proposed. I-DID is a research method to solve the dynamic decision process. It is based on the interactive partially observable Markov decision process (I-POMDP), which is an extension of the partially observable Markov decision process (POMDP) [11]. In I-POMDP, the deciding agent considers other agents as single decision-making subjects, rather than simply treating them as noise from the environment, as game theory does. This better matches reality. But I-POMDP also cannot express the decision process directly, and cannot solve the complex computation problem in the state space. Therefore, we choose I-DID

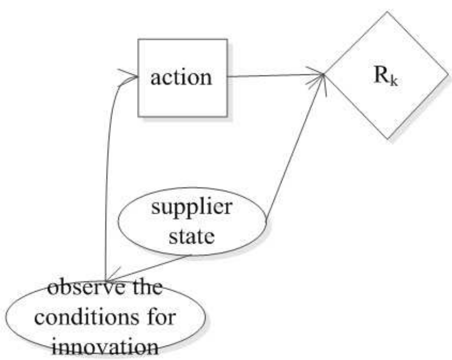

Figure 3: A Supplier ID Model

Table 4: Conditional Probability of Supplier's State Transfer Function

Interested	Disinterested
x_2	$1-x_2$

Table 5: Conditional Probability of Supplier's Observation Function

State	Mature Innovation Conditions	Immature Innovation Conditions
Interested	y_2	$1-y_2$
Disinterested	$1-y_2$	y_2

Table 6: Conditional Probability of Supplier's Value Function

Action	Interested	Disinterested
Cooperation	z_{21}	z_{22}
Non-Cooperation	z_{23}	z_{24}

Table 7: Conditional Probability of Service Enterprise's State Transfer Function

Interested	Disinterested
x_3	$1-x_3$

Table 8: Conditional Probability of Service Enterprise's Observation Function

State	Mature Innovation Conditions	Immature Innovation Conditions
Interested	y_3	$1-y_3$
Disinterested	$1-y_3$	y_3

Table 9: Conditional Probability of Service Enterprise's Value Function

Action	Interested	Disinterested
Innovation	z_{31}	z_{32}
Non-Innovation	z_{33}	z_{34}

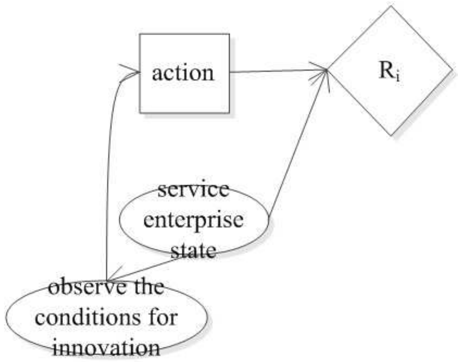

Figure 4: A Service Enterprise ID Model

to express the multi-agent decision-making process.

4.1 Interactive ID

Considering the service enterprise as the deciding agent, we generate an interactive ID as shown in Figure 5 [8]. Panel (a) shows the interactive ID of the l level, in which the model nodes $M_{j,l-1}$ and $M_{k,l-1}$ are represented by hexagons. In addition to the model nodes, there are also random nodes such as "*Action j*", "*Action k*" and dashed lines between them (called policy chains). The nodes "*Action j*", "*Action k*" are used to denote the probability distribution of the actions of j and k. The future state is the three-way interaction state, in which the observation i node represents the observation value of agent i, and the R_i node represents the value function of agent i.

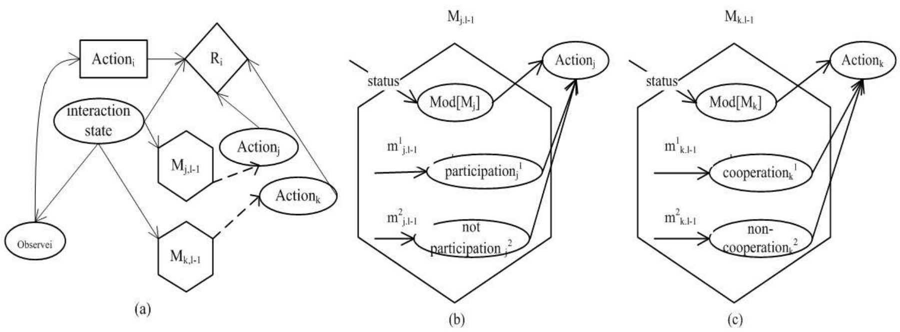

Figure 5: Interactive ID

Panel (b) shows the internal structure of the model nodes $M_{j,l-1}$. The model node $M_{j,l-1}$ contains the model of j on the *l-1* level, denoted as $m^1_{j,l-1}$, $m^2_{j,l-1}$. To solve each model, we obtain the corresponding optimal action set and its probability distribution, represented as "participation^1_j" and "non-participation^2_j" in Panel (b). Assume that the optimal action set obtained by solving $m^1_{j,l-1}$ is OPT, then the probability distribution of the action $Pr(a_j \in Action^1_j)=1/|OPT|(a_j \in OPT)$, otherwise 0. Therefore, the action nodes of *l-1* level interactive ID are transformed into the random nodes ("participation^1_j" and "non-participation^2_j" in the figure), and the probability distribution of the action a_j corresponding to the optimal policy is generated as $1/|OPT|(a_j \in OPT)$. In Figure 4, the corresponding action nodes ("participation^1_j" and "non-participation^2_j") and the node $Mod[M_j]$ are the parent nodes of the node "*Action j*". Since each action node corresponds to a model, the number of action nodes in the model nodes $M_{j,l-1}$ is the same as the number of models in the model node. The conditional probability distribution of the random node "*Action j*" uses the probability distribution of the action node "participation$_j^1$" or "non-participation$_j^2$". Furthermore, the value of *Mod[*M_j*]* selects the distribution of which node. Use the value of *Mod[*M_j*]* to distinguish between the different models of *j*. For example, when the value of *Mod[*M_j*]* is $m_{j,l-1}^1$, the random node "*Action j*" adopts the distribution of node "participation$_j^1$"; when the value of *Mod[*M_j*]* is $m_{j,l-1}^2$,the node "*Action j*" adopts "non-participation$_j^2$". The probability distribution of the node *Mod[*M_j*]* is the belief of the agent i to the j model. Panel (b) clarifies the concept of the strategy chain and we find that the strategy chain can be represented by the traditional ID arc (or edge). Panel (c) is similar to (b).

4.2 I-DID

The interactive ID is expanded in time to obtain I-DID, as shown in Figure 5 [8]. The dashed dotted arrow between model nodes is called the model update chain. The conditional probability distribution on random nodes "Interaction state^{t+1}" and "Observe^{t+1}" correspond to the state transfer function Ti and the observation function O_i in I-POMDP [10].

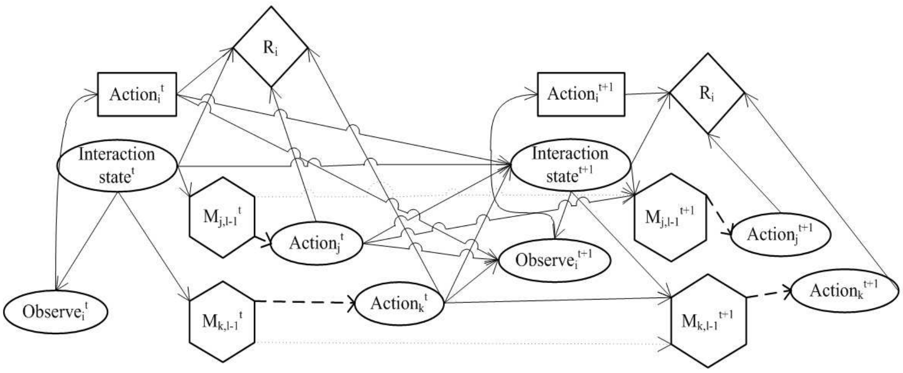

Figure 6: An I-DID of Service Innovation

Figure 6 [8] shows the implementation of the model update chain in I-DID with customer agent *agent j* as an example. Assuming that both models $m_{j,l-1}^1$ and $m_{j,l-1}^2$ of *agent j* at time t in level l produce only one optimal action, and assuming that the optimal actions are "participation" and "non-participation" respectively, then j may obtain two different observations: "innovation condition mature$_j^1$" and "innovation condition immature$_j^2$," then the model node contains four new models at time *t+1* ($m_{j,l-1}^{t+1,1}$, $m_{j,l-1}^{t+1,2}$, $m_{j,l-1}^{t+1,3}$, $m_{j,l-1}^{t+1,4}$ in the figure).Since j updates its belief through its actions and observations, the belief of these models is different. These four models represent the I-DIDs or DIDs on the *l-1* level, whose action nodes correspond to the random nodes "Action$_j^1$", "Action$_j^2$", "Action$_j^3$" and "Action$_j^4$" respectively. The supplier agent k is similar to the customer agent j.

4.3 DMU method

The solution of I-DID is very complicated. This is mainly because the number of candidate models in I-DID increases exponentially with time (as can be seen from Figure 7). The state space of S is the interactive state between agents. It is very large, and increases rapidly with the increase in the modeling nested layer number among agents. The existing solution algorithm is based on the principle of equivalent behavior (BE). The basic idea is that the behaviors of the two candidate models on agent j predicted by agent i are exactly the same, so we consider that the behaviors of the two models are equivalent. We can delete one model and assign the belief of the deleted model to the other model. The policy tree is used to represent the solution model, as seen in Figure 8. The left is the DID of a single agent j in two time slices, and the right is the corresponding policy tree. The policy tree of T time slices is represented by $\pi^T_{m_{j,l-1}}$; therefore, $OPT(m_{j,l-1}) \triangleq \pi^T_{m_{j,l-1}}$, in which $OPT(.)$ is the solution of the model. In the policy tree, each branch extends from the root node to the leaf node and is an action-observation sequence, represented by $h_j^{T-1}=\{a_j^t, o_j^{t+1}\}_{t=0}^{T-1}$. For example, there are two branches in Figure 7 [8]: "participation→ innovation condition mature→ participation" and "participation→ innovation condition immature→ non-participation".

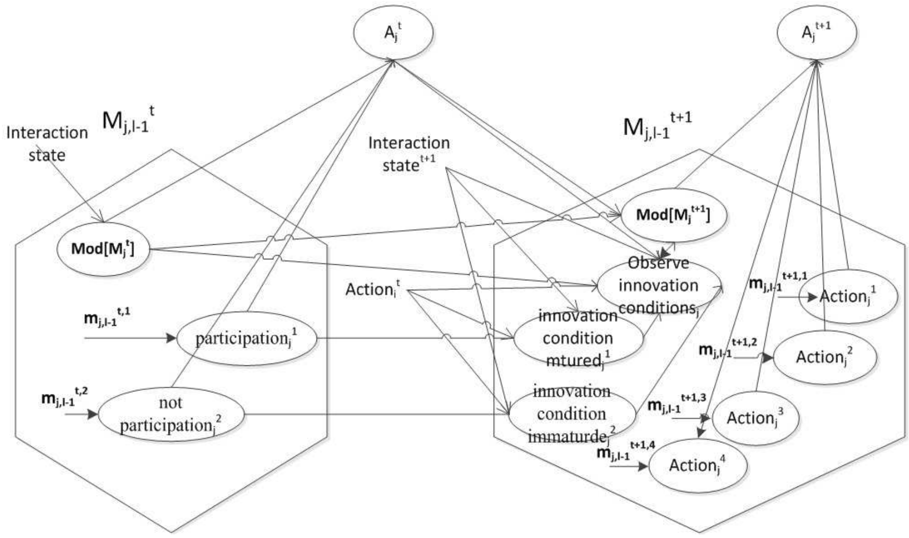

Figure 7: Realization of Model Update Chain in I-DID

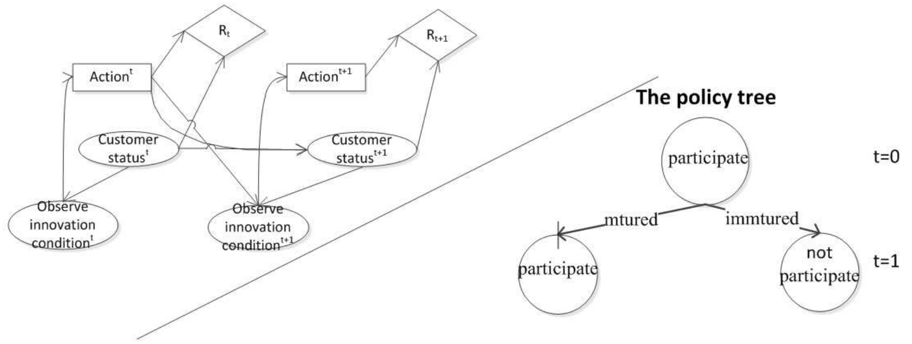

Figure 8: The Policy Tree and The Branch of ID

The bottom-up approach is used to solve I-DID, and the interactive ID to obtain the policy tree. Then we contrast the policy tree from top to bottom to check whether the models are behaviorally equivalent. The solution of the level 0 model is used by the traditional DID method; it provides a probability distribution for the corresponding action node of the level 1 I-DID.

One of the most effective methods based on the behavioral equivalence principle is the DMU method, which was proposed by Doshi and Zeng (2009) [7]. It obtains the minimum model set by merging the policy tree.

The minimum model set: $\hat{M}_{j,l-1}$ is the minimum model set of $M_{j,l-1}$, that is, for any $m_{j,l-1} \in \hat{M}_{j,l-1}$, there is no other model $m'_{j,l-1} \in \hat{M}_{j,l-1}/m_{j,l-1}$ and $OPT(m'_{j,l-1})=OPT(m_{j,l-1})$. The key of the DMU method is to get the minimum model set $\hat{M}_{j,l-1}$ and $\hat{M}_{k,l-1}$, that is, merge the policy tree from top to bottom, and obtain the policy graph [19].

Formally, let $\hat{m}_{j,l-1} \in \hat{M}_{j,l-1}$, then:

$$\hat{b}_i(\hat{m}_{j,l-1}|s) = \sum_{m_{j,l-1} \in \mathbb{M}_{j,l-1}} b_i(m_{j,l-1}|s) \tag{1}$$

where $b_{j,l-1}$ is the level l-1 belief, and $\mathbb{M}_{j,l-1} \subseteq M_{j,l-1}$ is the Build Extended model set in which the representative $\hat{m}_{j,l-1}$ is included.

Correspondingly, let $\hat{m}_{k,l-1} \in \hat{M}_{k,l-1}$, then:

$$\hat{b}_i(\hat{m}_{k,l-1}|s) = \sum_{m_{k,l-1} \in \mathbb{M}_{k,l-1}} b_i(m_{k,l-1}|s) \tag{2}$$

According to the DMU method solution, the multi-agent I-DID is modeled and solved in this paper. Assume that the 0-level models of agent j and k are both the DID, and x_1=0.5, x_2=-0.5, x_3=0.5, y_1=0.7, y_2=-0.7, y_3=0.7, z_{11}=8, z_{12}=-5, z_{13}=2, z_{14}=0, z_{21}=8, z_{22}=-5, z_{23}=2, z_{24}=0, z_{31}=8, z_{32}=-5, z_{33}=2, z_{34}=0, r_{11}=8, r_{12}=5, r_{13}=2, r_{14}=5, r_{15}=3, r_{16}=2, r_{17}=2, r_{18}=1, r_{21}=-1, r_{22}=-3, r_{23}=-5, r_{24}=-3, r_{25}=1, r_{26}=0, r_{27}=0, r_{28}=-1, m=0.85, n=0.85, and x=0.5, in which the interactive state number is 2, the action number of agent i, j and k are all 2, the observation number of agent i is 8, and the observation number of agent j and k are both 2. The initial model numbers N=25 and N=50 are used to solve the model respectively [16].

Table 10: DMU Method's Speed

Level 1	N	Agent Number	T	DMU Times
Solve The 0-Level Model	25	2	3	124
	50	2	3	215
	25	2	5	652
	50	2	5	1247
	25	3	3	96
	50	3	3	160
	25	3	5	552
	50	3	5	987
BE Model	25	2	3	24
	50	2	3	24
	25	2	5	52
	50	2	5	52
	25	3	3	132
	50	3	3	132
	25	3	5	9087
	50	3	5	9087

In Table 10, N represents the initial model number, T represents the number of time slices, and the DMU time unit is seconds. It can be seen that the time required to solve and extend the multi-agent I-DID model of three agents is much larger than that of two agents. In other words, if we only build a model only between the service enterprise and customer or between the service enterprise and supplier, the process is much faster and the length of time slice is much longer. However, the service enterprise must consider the combined effect of both the supplier and customer; it must establish three agent models. In the 0-level model, the number of agents has no relationship with the speed; this is because we assume that the three agents I-DID of the 0-level model is the DID. So it is the same as the two agent model; only, we need to consider another agent, such as customer or supplier.

The solution of the model is Figure 9, in which (a) is the result of three time slices; (b) is the result of five time slices; DMU 25 is the result of the DMU method, where the initial model is 25; DMU 50 is also considered. The abscissa represents the value of , and the ordinate represents the average value obtained by the service enterprise. When T=3 in the figure, each average is the average of 10 one thousand game income values. When T=5, each average is the average of 10 one hundred game income values. It can be seen from the figure that the average value increases with decreasing, until it approaches the exact algorithm. When the initial model N=50, the average value is generally higher than N=25, that is to say, the more models there are, the greater the gain. Furthermore, the average value increases as the time slice increases, and the accuracy of decisions improves. But with the increase of the time slice and the initial model, the solution speed becomes progressively slower until it cannot be solved. Therefore, we need to choose the appropriate time slice and initial model number.

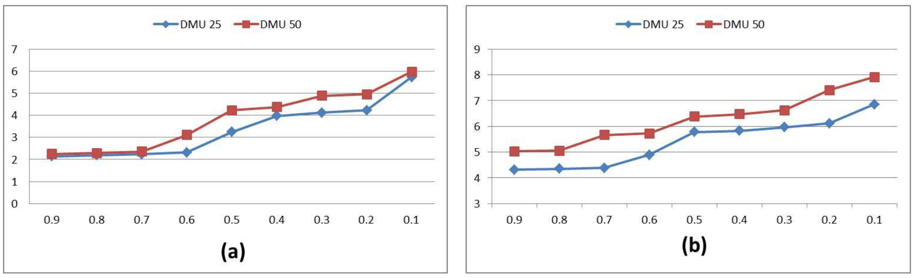

Figure 9: Comparison of Model Solving Results

It can be seen from the results of the above model that the quality of decisions made by service enterprises, customers, and suppliers in service innovation is related to the number of time slices and the initial model. Because I-DID is an individual decision-making method, it considers a problem from a single agent perspective, unlike the Nash equilibrium as a whole, such as game theory, since the service enterprise is the main agent in this case. Of course, the customer or supplier can also be considered the main agent. In the process of model solving, suppose the environment state is "interested", the customer decision action is "participation" and the supplier decision action is "cooperation", the service enterprise's decision-making action should be "innovation;" in such a case, making the decision will obtain the maximum return value of 8. Suppose the environment state is "disinterested", the customers' decision action is "non-participation" and the supplier's decision action is "non-cooperation", then the service enterprise's decision-making action should be "non-innovation"; "innovation" will be the worst action as the probability of innovation failure is great, and we obtain the maximum penalty value of -5. The setting of the data is the hope of the enterprise to innovate; this is mainly because there is no way out without innovation [13]. There could be mistakes in the innovation process, but it also allows enterprises to accumulate experience. Consequently, the reward of innovation is greater than the punishment of innovation failure. Setting x=0.5 means that customer, service enterprise, and supplier initially have no preference for the maturity of the innovation condition. This is an a priori Bayesian probability that becomes gradually more ineffective as the time slice increases. When m=0.85, it means that the customer wants to participate with an accuracy of 0.85, and the corresponding value of n indicates the accuracy of the observation of supplier cooperation. At each time slice, the service enterprise will make a decision about whether to innovate or not, and will then obtain a corresponding reward or penalty value. With a longer time slice, the communication between the service enterprise and the customer or supplier increases the gradual understanding of the environment and the opponent increases the probability of making the right decision, and the return value increases. The more models for each agent, the bigger the return value and the ability to solve the problem is greatly tested. So the number of initial candidate models is the key to the quality of the decision-making.

5 Conclusion

First, service innovation is not an end in itself, but a means to an end, because the enterprise needs the benefit. The enterprise should decide whether or not to innovate for its own benefit.

Second, the initial degree of interest from the customer and supplier is only an a priori probability. After many decisions, it tends to a stable value, which means there is no direct relationship between the initial interest of the customer and supplier and the final innovation results. Different initial values only affect the speed of the solution.

Third, if the service enterprise takes more time to make the decision, the effect of the innovation will be more ideal. As time progresses, multiple decisions will make the effect of the innovation more desirable.

Lastly, the more customer and supplier factors that the service enterprise considers, the more reasonable its decision will be. At the same time, we should not blindly consider too many factors for the sake of rationality, since this may slow down the decision-making speed of the enterprise, thus affecting the efficiency of service innovation.

In summary, a service enterprise should consider its own innovation conditions and then continue communicating with the customer and supplier, predicting possible reactions between them, correcting the innovation decision, and improving the quality and benefit of service innovation.

Funding

This research was supported by the National Natural Science Foundation of China (No. 61562033); the Natural Science Foundation of Jiangxi Province (No. 20142BBE50038, No. 20161BBF60090, No. 20171BAB202022); and the Social Science Planning Project (No. 16GL20) of Jiangxi Province.

Bibliography

[1] Andres, B.; Poler, R.; CamarinhaMatos, L. M.; Afsarmanesh, H.(2017); A Simulation Approach to Assess Partners Selected for a Collaborative Network;*International Journal of Simulation Modelling*, 16(3), 399–411, 2017.

[2] Aranda, D.A.; Molina–Fernández, L.M. (2002); Determinants of innovation through a knowledge-based theory lens, *Industrial Management* & *Data Systems*, 102(5), 289–296, 2002.

[3] Bilderbeek, R.; Hertog, P.D.; Marklund, G.; Miles I. (1998); Services in innovation - Knowledge intensive business services (KIBS) as co-producers of innovation, *Synthesis report, SI4S project*, 1998.

[4] Burns, T.E.; Stalker, G.M. (2009); The Management of Innovation, *Quarterly Journal of Economics*, 109(4), 1185–1209, 2009.

[5] Dai, Y.; Wu, W.; Zhou, H.B.; Zhang, J.; Ma, F.Y. (2018); Numerical Simulation and Optimization of Oil Jet Lubrication for Rotorcraft Meshing Gears, *International Journal of Simulation Modelling*, 17(2), 318–326, 2018.

[6] Dai, Y.; Zhu, X.; Zhou, H.; Mao, Z.; Wu, W. (2018); Trajectory Tracking Control for Seafloor Tracked Vehicle By Adaptive Neural-Fuzzy Inference System Algorithm, *International Journal of Computers Communications & Control*, 13(4), 465–476, 2018.

[7] Doshi, P.; Zeng, Y.F. (2009); Improved Approximation of Interactive Dynamic Influence Diagrams Using Discriminative Model Updates, *International Conference on Autonomous Agents and Multiagent Systems*, 907–914, 2009.

[8] Doshi, P.; Zeng, Y.F.; Chen, Q. (2009); Graphical models for interactive POMDPs: representations and solutions, *Autonomous Agents and Multi-Agent Systems*, 18(3), 376–416, 2009.

[9] Gallouj, F. (2015); Innovation in the Service Economy-The New Wealth of Nations, *Post-Print*, 2015.

[10] Gmytrasiewicz, P.J.; Doshi, P. (2005); A Framework for Sequential Planning in Multi-Agent Settings, *Journal of Artificial Intelligence Research*, 24(1), 49–79, 2005.

[11] Kaelbling, L.P.; Littman, M.L.; Cassandra, A.R. (1998); Planning and Acting in Partially Observable Stochastic Domains, *Artificial Intelligence*, 101(1-2), 99–134, 1998.

[12] Koller, D.; Milch, B.(2001) ; Multi-agent influence diagrams for representing and solving games, *International Joint Conference on Artificial Intelligence*, 1027–1034, 2001.

[13] Ojasalo, K.; Koskelo, M.; Nousiainen, A.K. (2015), Foresight and Service Design Boosting Dynamic Capabilities in Service Innovation, *The Handbook of Service Innovation*, Springer London, 193–212, 2015.

[14] Pan, Y.H.; Luo, J.; Zeng. Y.F. (2012); Modeling Method of Multi - Agent Interactive Dynamic Impact Diagram, *Journal of Xiamen University (Natural Science)*, 51(6), 985–990, 2012.

[15] Pan, Y.H.; Zeng, Y.F. (2018); Interactive Dynamic Influence Diagram Research Summary and New Solutions on Top-K Model Selection, *Chinese Journal of Computer*, 41(1), 28–46, 2018.

[16] Pan, Y.H.; Zeng, Y.F.; Xiang, Y.P.; Sun, L.; Chen, X.F. (2015); Time-Critical Interactive Dynamic Influence Diagram, *International Journal of Approximate Reasonin*, 57, 44–63, 2015.

[17] Ryu, H.S.; Lee, J.N.; Choi, B. (2015); Alignment Between Service Innovation Strategy and Business Strategy and Its Effect on Firm Performance: An Empirical Investigation, *IEEE Transactions on Engineering Management*, 62(1), 100–113, 2015.

[18] Zeng, Y.F.; Doshi, P. (2012); Exploiting Model Equivalences for Solving Interactive Dynamic Influence Diagrams, *Journal of Artificial Intelligence Research*, 43(1), 211–255, 2012.

[19] Zeng, Y.F.; Doshi, P.; Chen Y.K.; Pan Y.H.; Mao H.; Chandrasekaran M. (2016) ; Approximating behavioral equivalence for scaling solutions of I-DIDs, *Knowledge and Information Systems*, 49(2), 511–552, 2016.

[20] Zhang, H.Q.; Lu, R.Y. (2013); The impact of customer participation on employee's innovation behavior in the service industry, *Science Research Management*, 34(3), 99–105, 2013.

[21] Zhang, R.Y.; Liu, X.M.; Wang, H.Z.; Nie, K. (2010); Customer-Firm Interaction and Service Innovation Performance: A Perspective of Organizational Learning from Customers, *Chinese Journal of management*, 7(2), 218-224, 2010.