A graph model with minimum cost to support conflict resolution and mediation in technology transfer of new product co-development

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***Abstract*—Successful new product development advocate for collaboration among different institutions in which technology transfer dispute widely exists. Although several studies have discussed conflict modelling and resolution in technology transfer dispute, scant research attempted to model third-party (or mediator) mediation, let alone develop effective approaches to minimize cost in the conflict resolution process. This study uses a graph model and minimum cost to investigate the conflict resolution and mediation in technology transfer dispute of new product collaborative development. On the one hand, the conflict in technology transfer of new product collaborative development is modelled using the graph model theory, in which the stakeholders (or decision-makers), their options, the feasible states, and the preferences of decision-makers are analyzed. On the other hand, an inverse graph model with minimum cost is designed to tackle the problem of specifying which decision-makers' preferences lead to a desired solution, thereby making it easier for a mediator or other third party to influence the course of the conflict. In the inverse graph model with minimum cost, two 0-1 mixed linear approaches are constructed to judge the Nash and General Merataionality stabilities within the graph model, and several optimization-based models that minimize mediation cost are designed for the mediator to guide the technology transfer conflict resolution process to achieve the desired solution. Finally, the proposed methodology is applied to a technology transfer dispute case study.**

***Index Terms* — Group decisions and negotiations; new product development; conflict resolution and mediation; graph model; technology transfer**

I. Introduction

Shortening product life cycles, fierce market competition, insatiable consumer appetites and changing consumer demands have forced companies to develop new products to succeed or survive [29, 35, 53]. New product development is broadly described as the transformation of embryonic ideas into saleable products, which apply to both tangible products (something physical that can be touched, such as computers, automobiles, and phones) and intangible products (such as services, apps, and software programs) [7, 8, 16, 23].

Collaboration is an essential driver of new product development [40, 45], especially complex product development [37]. A key common aspect of new product co-development (NPCD) is technology transfer, which affects the product development process and has attracted the interest of many researchers. For example, Hsu et al. [21], taking Taiwan's universities as a research base, designed a methodology to identify the relative importance of performance drivers in enhancing the outcome of university technology transfer by improving internal administration processes and procedures; while Villani et al. [47] proposed a proximity-based methodology to analyze the impact mechanism of intermediary organizations on technology transfer. Chen et al. [6] conducted a comprehensive literature review and taxonomy of university technology transfer in China.

Conflicts often occur during the technology transfer process in the NPCD because technology exporters and importers often have different goals, which affect the realization of technology transfer and the NPCD. Numerous approaches have been proposed for analyzing technology transfer disputes (e.g., [10, 50]). Alexander et al. [1] utilized meta-rules to overcome barriers to knowledge transfer in university–industry collaboration. Mathieu [36] investigated conflicts of interest in university technology transfer. Huang [22] proposed a SWOT (strengths, weaknesses, opportunities and threats) based approach to analyze small and medium-sized enterprises' environmental technology transfer conflicts from Sweden to China. Kaufmann and Roessing [24] studied intra-organizational technology transfer conflicts between headquarters and their foreign subsidiaries in emerging markets that lack the protection of intellectual property rights. Fan [11] proposed a general theoretical framework to reconcile conflicting perspectives on North-South technology transfer.

Throughout history, third-party mediation has been vital in resolving of conflicts. This has become increasingly evident in the last century, since about 70% of conflicts have attracted third-party intervention [5]. For example, the famous Consensus Building Institute (CBI, https://www.cbi.org) is committed to solving conflicts among global governments, organizations and individuals. An analysis of practical product co-development reveals the need for a comprehensive approach to model and analyze the intervention of a third party in a conflict. For example, university-industry collaboration in developing new products is common in competitive commercial markets [6]. When a university-industry collaboration conflict occurs, the university technology transfer office must often guide the negotiation process to eliminate the conflict. Although much research has addressed NPCD conflict modelling, little work has been carried out on modelling third party (or mediator) mediation. In general, the mediator is interested in guiding decision-makers to alter their preferences to achieve desirable stable scenarios, and providing incentives to decision makers is an

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effective way to conduct this work [41, 46]. In other words, conflict mediation often implies some "cost" to the decision-makers associated with people's general unwillingness to change preferences. Moreover, the mediator is interested in having the lowest possible cost to achieve his/her goal [41, 46]. Therefore, designing an approach to support conflict resolution and mediation in NPCD technology transfer that considers mediation costs is necessary.

The graph model, a methodology to study and analyze strategic interactions among two or more decision-makers, has been expanded for conflict resolution since its development in the mid-1980s [12, 25, 26] because it allows the prediction of the most likely outcome by strategically analyzing moves and counter moves in a conflict. Many significant improvements have been made to the graph model over the last three decades, which include the following aspects: (i) option prioritization to obtain the preference orderings of feasible states for every decision-makers in the conflict [4, 34, 43, 55]; (ii) stability analysis including Nash stability [38], general metarationality (GMR) [20], symmetric metarationality (SMR) [20], sequential stability (SEQ) [13], and symmetric sequential stability (SSEQ) [42]; (iii) coalition analysis, including coalition formation, preference of a coalition and definitions of coalition stabilities, among others [17, 33, 61, 62]; (iv) matrix representation of solution concepts to judge stabilities within the graph model [44, 48, 52]; (v) different preference modelling of decision-makers opinions [2, 3, 51]: crisp preference [34], unknown preference [32], and fuzzy preference [51]; (vi) the influence of attitudes and behaviors of decision makers on the decision makers' preferences and the equilibria of a conflict [49, 60]; and (vii) the inverse graph model to address the problem of specifying which decision-makers' preferences lead to a particular resolution [14, 15, 27, 48].

Recently, Rêgo et al. [41] and Tao et al. [46] proposed optimization-based inverse graph models by adding "cost" to the mediation process. Inspired by the advances on graph models, particularly in the minimum cost inverse graph model [41, 46], this study proposes an inverse graph model with minimum cost to support conflict resolution and mediation in NPCD technology transfer. First, the main components involved in the technology transfer conflict within the graph model are modelled: the decision-makers (or stakeholders), their options, feasible states, and the preferences of the decision-makers. Then, two commonly used stable concepts, the Nash and GMR stabilities, were adopted to analyze and predict the technology transfer conflict outcome, and two 0-1 mixed linear approaches are presented to judge these two stabilities. Subsequently, two mediation cost optimization-based models are designed and transformed into 0-1 mixed linear programming models to facilitate their resolution in supporting the mediator to guide the technology transfer conflict resolution process to achieve the desired solution under Nash or GMR stabilities. An NPCD case study was presented to demonstrate the validity of the proposed approach.

The remainder of this paper is arranged as follows. Section II introduces the basic knowledge regarding graph models and additive preference relations. Next, Section III proposes a graph model with minimum cost for technology transfer conflict resolution in an NPCD. Section IV presents a technology-transfer conflict case study demonstrating the use of the proposed methodology. Additionally, the graph model with minimum cost is analyzed via numerical and comparison analysis in Section V. Finally, Section VI concludes the paper and discusses future research directions.

II. Preliminaries

The present study requires the introduction of basic knowledge of the structure and stability concepts of the graph model, as well as the additive preference relation.

A. Basics of the graph model

The graph model is a methodology for modelling and analyzing strategic disputes between two or more decision-makers with contradictory objectives [19, 26]. The key components of the graph model are: a set of decision makers, $E=\{E_1, E_2, ..., E_m\}$ $(m \ge 2)$; a set of feasible states or scenarios, $S=\{s_1, s_2 ..., s_h\}$ $(h \ge 2)$; the decision maker's own directed graph, and preferences for the feasible states [3, 25, 26]. Let $M=\{1, 2, ..., m\}$ and $H=\{1, 2, ..., h\}$. Common to all the decision-makers, the feasible states are represented as nodes in the directed graphs of the decision-makers. The (directed) arcs of a decision-maker's graph are the possible state-to-state moves controlled by the decision-maker. In the graph model, the decision-makers' preferences affect stability.

The graph model for conflict resolution can be formally represented as $<E, S, \{(D^k, PO^k): E_k \in E\}>$. The decision-maker's directed graph model is $D^k=(S, T^k)$ with T^k being the set of moves controlled by the decision-maker $E_k \in E$. A move by a decision maker is usually expressed as an ordered pair of states: $(s_i, s_j) \in T^k$ means the decision-maker E_k can cause the conflict to move (directly) from s_i to s_j . The preference ordering of decision-maker E_k over $S=\{s_1, s_2 ..., s_h\}$ is $PO^k=(po_1^k, po_2^k, ..., po_h^k)^T$, where $po_i^k < po_j^k$ means that state s_i is better than s_j , i.e. $s_i \succ_k s_j$, while $po_i^k = po_j^k$ represents equally important states s_i and s_j , i.e. $s_i \sim_k s_j$.

The definitions of the two basic graph model stability concepts, Nash and GMR stabilities, are provided below. These stability definitions depend on the concepts of available moves (or counter-moves) as well as on unilateral improvements from an initial state by a decision-maker (or a group of decision-makers).

Definition 1 [26]: The decision maker E_k reachable list of states from a state $s_t \in S$, denoted by $R^k(s_t)$, is the set of states decision maker E_k can attain from s_t in one move. Mathematically, $R^k(s_t)=\{s_i \in S: (s_t, s_i) \in T^k\}$. An element of $R^k(s_t)$ is called a unilateral move from s_t , which is controlled by the decision-maker E_k .

Let $\| R^k(s_t) \|$ be the cardinality of the $R^k(s_t)$. State is a unilateral improvement from $s_t \in S$ by E_k , if $s_i \in R^k(s_t)$ and $po_i^k < po_t^k$. The set of all unilateral improvements from s_t by E_k is denoted $R^{k,+}(s_t)$.

Definition 2 (Nash Stability [12, 26]): State s_t is Nash stable state for E_k iff $R^{k,+}(s_t)=\phi$. State s_t is a Nash equilibrium iff s_t is Nash stable state for all decision-makers.

Definition 3 (GMR Stability [12, 26]): State s_t is a GMR stable state for E_k iff for every $s_i \in R^{k,+}(s_t)$, there exists an $s_j \in R^{M-\{k\}}(s_i)$ such that $po_t^k \le po_j^k$, where $R^{M-\{k\}}(s_i)$ denotes the set of states that E_k ' opponents can attain from s_i by a subsequent legal sequence of moves. State s_t is a GMR equilibrium state iff s_t is a GMR stable state for all decision-makers.

Definitions 2 and 3 are used to judge whether a state is in Nash or GMR equilibrium, respectively. If none of the states is in the Nash or GMR equilibria, there is no Nash or GMR equilibrium in the conflict problem.

B. Additive preference relation

Different preference representation structures have been developed, such as the linguistic preference relation [31], additive preference relation (also called fuzzy preference relation [39]), and preference–approval structure [9]. The additive preference relation is a widely used preference representation structure adopted in this study.

The concept of an additive preference relation over a set of objects $X=\{x_1,x_2,...,x_n\}$, and its consistency level are provided below.

Definition 4 [39]: Given a set X of cardinality n, a matrix $A=(a_{ij})_{n\times n}$ with the elements $a_{ij}\in[0,1]$ representing the preference intensity of object x_i over object x_j, and $a_{ij}+a_{ji}=1\ \ \forall i,j=1,2,...,n$, is called an additive preference relation over X.

Definition 5 [18]: The consistency level of the additive preference relation $A=(a_{ij})_{n\times n}$ is measured using the following expression:

$$CL(A)=1-\frac{4}{n(n-1)(n-2)}\sum_{i,j,z=1;i<j<z}^{n}|a_{ij}+a_{jz}-a_{iz}-0.5| \qquad (1)$$

It is easy to prove that $CL(A)\in[0,\ 1]$. The larger $CL(A)$ value means a better consistency level of matrix $A=(a_{ij})_{n\times n}$. In general, the consistency level of matrix $A=(a_{ij})_{n\times n}$ is considered acceptable if it satisfies $CL(A)\geq\alpha$, where $\alpha\in[0,1]$ denotes a predefined threshold value.

The priority vector for $X=\{x_1,x_2,...,x_n\}$ obtained from $A=(a_{ij})_{n\times n}$ is denoted as $PV=(pv_1,\ pv_2,\ ...,\ pv_n)^T$, where ties are allowed. Similar to the method for computing the priority vector of the interval additive preference relation [30], we adopted the following method to compute pv_i:

$$pv_i=\frac{2}{n^2-n}\sum_{j=1,j\neq i}^{n}a_{ij} \qquad (2)$$

The larger the value of pv_i, the better the object x_i is. From PV, the preference ordering $PO=(po_1,po_2,...,po_n)^T$ can be obtained, where $po_i=g$ if pv_i is the gth largest value in $\{pv_1,pv_2,...,pv_n\}$. For example, if $PV=(0.2,\ 0.3, 0.35, 0.15)^T$, then $PO=(3,\ 2,\ 1,\ 4)^T$.

III. The Graph Model with Minimum Cost for Technology Transfer Conflict Resolution

This section presents a resolution framework for technology transfer conflicts in the NPCD process. Technology transfer disputes are frequent in the NPCD and significantly impact product development. A third party or mediator is usually required to address technology transfer disputes. To help a mediator find an optimal way to resolve a technology transfer conflict, the following two key research questions must be answered:

(1) What is the stable state of technology transfer dispute in the NPCD? Answering this question allows us to analyze whether the desired state is stable.

(2) If the desired state cannot be achieved under the given stable concept, how can we tackle the problem of specifying which decision-makers' preferences lead to a desired solution, thereby making it easier for the mediator to influence the resolution course of the technology transfer conflict.

Motivated by the answers to these research questions, this study presents an inverse graph model framework with a minimum cost, as shown in the following (see Fig. 1). There are three key processes in the proposed resolution framework: modelling, stability analysis, and use of the inverse approach with minimum cost. These procedures are described in detail in the following sections.

A. Modelling

Technology transfer dispute in the NPCD can be formally represented as the tuple $<E,\ S,\ \{(D^k,\ PO^k):\ E_k\in E\}>$ that consists of decision makers, feasible states, directed graph models, and decision-maker's preferences. The theoretical formalization and detailed analysis of the tuple components are provided below:

(1) Identification of the decision-makers involved in the technology transfer conflict. The first task is to identify stakeholders (or decision-makers) involved in the technology transfer conflict of the NPCD: $E=\{E_1,\ E_2,\ ...,\ E_m\}\ \ (m\geq2)$.

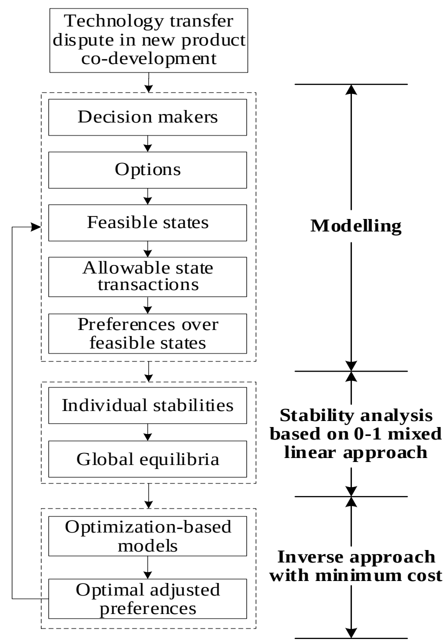


Fig. 1. The inverse graph model framework with minimum cost

(2) Identification of decision-makers' options. An option is the course of action that the decision-maker may or may not choose to pursue. The set of options associated with decision-maker E_k in the technology transfer dispute in the NPCD is denoted as $O^k=\{o_1^k,\ o_2^k\ ...,\ o_{h^k}^k\}$.

(3) Identification of the feasible states. The $S=\{s_1,\ s_2\ ...,\ s_h\}$ $(h\geq2)$ is a set of feasible states in the technology transfer conflict of the NPCD. Each state is defined as a combination of options reflecting participating decision-makers' strategies to secure individual goals. Therefore, a state is modelled as an ordered column tuple of Ys and Ns, or 1s and 0s, in which each entry corresponds to an option; Y (or 1) is recorded if the option is chosen, otherwise N (or 0) is recorded. Specifically, the states are formed after all decision makers make a choice from their options O^k. Through analysis, some infeasible states can be eliminated.

(4) Identification of the allowable state transactions. The decision-maker's directed graph is denoted by $D^k=(S,\ T^k)$, where T^k represent the set of moves controlled by decision-maker E_k in the technology transfer conflict in the NPCD.

(5) Preference analysis. Recently, additive preference relations, $A^k=(a_{ij}^k)_{h\times h}$, have been adopted in graph models to capture the preferences of decision-makers, $E_k \in E$, over a set of feasible states S (e.g., [2, 3]).

B. Stable analysis: 0-1 mixed linear approach

In this section, we design several 0-1 mixed linear approaches to the represent different stabilities within the graph model based on the use of additive preference relations.

(1) 0-1 mixed linear approach to Nash stability

Based on Eq. (2), for each additive preference relation, $A^k = (a_{ij}^k)_{h\times h}$, the corresponding priority vector, $PV^k = (pv_1^k, ..., pv_h^k)^T$, is derived.

An approach for representing Nash stability via a series of 0-1 mixed linear constraints is developed below.

Lemma 1: Let

$$x_{ti}^k = \begin{cases} 1, & pv_t^k \geq pv_i^k \\ 0, & pv_t^k < pv_i^k \end{cases}, \quad s_i \in R^k(s_t) \tag{3}$$

Then, we have:

(i) The state s_t is Nash stable for decision-maker E_k iff $\sum_{s_i \in R^k(s_t)} x_{ti}^k = \| R^k(s_t) \|$;

(ii) The state s_t is globally Nash stable iff $\sum_{k=1}^{m} \sum_{s_i \in R^k(s_t)} x_{ti}^k = \sum_{k=1}^{m} \| R^k(s_t) \|$.

The proof of **Lemma 1** is in the Appendix.

Lemma 2: The 0-1 variable $x_{ti}^k \ (s_i \in R^k(s_t))$ used in **Lemma 1** can be determined using the following constraints:

$$\begin{cases} pv_t^k - pv_i^k < Z \cdot x_{ti}^k & (a) \\ pv_t^k - pv_i^k \geq Z \cdot (x_{ti}^k - 1) & (b) \\ x_{ti}^k \in \{0,1\} & (c) \end{cases}. \tag{4}$$

where Z is an adequately large number.

The proof of Lemma 2 is in the Appendix.

Lemmas 1 and **2** provide a 0-1 mixed linear approach to determine the Nash stable state within the graph model framework.

(2) 0-1 mixed linear approach to GMR stability

A 0-1 mixed linear approach was developed to represent the GMR stability. For convenience, the following notation is introduced: $\bar{R}^k(s_t) = \{s_i \mid s_i \in R^k(s_t) \text{ and } R^{M-\{k\}}(s_i) = \phi\}$ and $\bar{\bar{R}}^k(s_t) = \{s_i \mid s_i \in R^k(s_t) \text{ and } R^{M-\{k\}}(s_i) \neq \phi\}$, where $R^{M-\{k\}}(s_i)$ denotes the states transferred from state s_i controlled by decision makers $\{E_1, E_2, ..., E_m\}$ but not by decision-maker E_k in one move.

Lemma 3: Let x_{ti}^k, y_{tij}^k, and z_{ti}^k be the following 0-1 variables:

$$\begin{cases} x_{ti}^k = \begin{cases} 1, & pv_t^k \geq pv_i^k \\ 0, & pv_t^k < pv_i^k \end{cases}, \quad s_i \in \bar{R}^k(s_t) \\ y_{tij}^k = \begin{cases} 1, & pv_t^k \geq pv_i^k \\ 0, & pv_t^k < pv_i^k,\ pv_t^k < pv_j^k \\ 1, & pv_t^k < pv_i^k,\ pv_t^k \geq pv_j^k \end{cases}, \quad s_i \in \bar{\bar{R}}^k(s_t);\ s_j \in R^{M-\{k\}}(s_i) \\ z_{ti}^k = \begin{cases} 1, & \sum_{s_j \in R^{M-\{k\}}(s_i)} y_{tij}^k \geq 1 \\ 0, & \sum_{s_j \in R^{M-\{k\}}(s_i)} y_{tij}^k = 0 \end{cases}, \quad s_i \in \bar{\bar{R}}^k(s_t) \end{cases} \tag{5}$$

(i) The state s_t is GMR stable for decision-maker E_k iff $\sum_{s_i \in \bar{R}^k(s_t)} x_{ti}^k + \sum_{s_i \in \bar{\bar{R}}^k(s_t)} z_{ti}^k = \| R^k(s_t) \|$.

(ii) The state s_t is globally GMR stable iff

$$\sum_{k=1}^{m} \left(\sum_{s_i \in \bar{R}^k(s_t)} x_{ti}^k + \sum_{s_i \in \bar{\bar{R}}^k(s_t)} z_{ti}^k \right) = \sum_{k=1}^{m} \| R^k(s_t) \|.$$

The proof of **Lemma 3** is in the Appendix.

Lemma 4: Let x_{ti}^k, y_{tij}^k, and z_{ti}^k be the 0-1 variables defined in Lemma 3. Then:

(i) $x_{ti}^k \quad (s_i \in \bar{R}^k(s_t))$ is determined by the following set of constraints:

$$\begin{cases} pv_t^k - pv_i^k < Z \cdot x_{ti}^k & (a) \\ pv_t^k - pv_i^k \geq Z \cdot (x_{ti}^k - 1) & (b) \\ x_{ti}^k \in \{0,1\} & (c) \end{cases}. \tag{6}$$

(ii) $y_{tij}^k \quad (s_i \in R^k(s_t),\ s_j \in R^{M-\{k\}}(s_i))$ is determined by the following set of constraints:

$$\begin{cases} pv_t^k - pv_i^k < Z \cdot w_{ti}^k & (a) \\ pv_t^k - pv_i^k \geq Z \cdot (w_{ti}^k - 1) & (b) \\ pv_t^k - pv_j^k < Z \cdot u_{tj}^k & (c) \\ pv_t^k - pv_j^k \geq Z \cdot (u_{tj}^k - 1) & (d) \\ w_{ti}^k + u_{tj}^k - 0.5 < Z \cdot y_{tij}^k & (e) \\ w_{ti}^k + u_{tj}^k - 0.5 > Z \cdot (y_{tij}^k - 1) & (f) \\ w_{ti}^k, u_{tj}^k, y_{tij}^k \in \{0,1\} & (g) \end{cases}. \tag{7}$$

(iii) $z_{ti}^k \quad (s_i \in \bar{\bar{R}}^k(s_t))$ is determined by the following set of constraints:

$$\begin{cases} \sum_{s_j \in R^{M-\{k\}}(s_i)} y_{tij}^k - 0.5 < Z \cdot z_{ti}^k & (a) \\ \sum_{s_j \in R^{M-\{k\}}(s_i)} y_{tij}^k - 0.5 \geq Z \cdot (z_{ti}^k - 1) & (b) \\ z_{ti}^k \in \{0,1\} & (c) \end{cases} \tag{8}$$

The proof of Lemma 4 is in the Appendix.

Because a series of linear constraints with continuous variables and 0-1 variables are used, the approaches for representing the Nash and GMR stabilities are called 0-1 mixed linear approaches.

C. Inverse approach with minimum cost

Let s_t be the desirable state in an NPCD technology transfer dispute. Two inverse graph models with minimum cost based on Nash and GMR stabilities were designed to tackle the problem of specifying which preferences for decision-makers lead to state s_t, thereby making it easier for a mediator (or other third parties) to influence the course of the NPCD technology transfer conflict.

(1) Minimum cost inverse graph model based on Nash stability

As analyzed in the above sections, the decision-makers' preferences influence the stability of the NPCD technology transfer conflict to achieve the desired solution, and the mediator often needs to guide the decision-makers in adjusting their preferences. Let $\overline{A^k} = (\overline{a_{ij}^k})_{h\times h}$ be the adjusted additive preference relation associated with $A^k = (a_{ij}^k)_{h\times h} \quad (k \in M)$. If s_t is Nash stable, then $s_t \succ_k s_i$ for $k \in M$ and $s_i \in R^k(s_t)$, which means that:

$$\begin{cases} \overline{pv_t^k} - \overline{pv_i^k} < Z \cdot x_{ti}^k \\ \overline{pv_t^k} - \overline{pv_i^k} \geq Z \cdot (x_{ti}^k - 1) \\ x_{ti}^k \in \{0,1\} \\ \sum_{s_i \in R^k(s_t)} x_{ti}^k = \| R^k(s_t) \| \end{cases}. \tag{9}$$

where

$$\overline{pv_i^k} = \frac{2}{h^2 - h} \sum_{j=1, j\neq i}^{h} \overline{a_{ij}^k} \tag{10}$$

Meanwhile, the consistency level of $\overline{A^k}$ is to be acceptable, i.e. $CL(\overline{A^k}) \geq \alpha$:

$$CL(\overline{A^k}) = 1 - \frac{4}{h(h-1)(h-2)} \sum_{i,j,z=1; i<j<z}^{h} | \overline{a_{ij}^k} + \overline{a_{jz}^k} - \overline{a_{iz}^k} - 0.5 | \geq \alpha \tag{11}$$

Naturally, the mediation cost between $\{A^1, A^2, ..., A^m\}$ and $\{\overline{A^1}, \overline{A^2}, ..., \overline{A^m}\}$ is to be optimized:

$$\min \sum_{k=1}^{m} \sum_{i=1}^{h-1} \sum_{j=i+1}^{h} c_k \cdot |a_{ij}^k - \overline{a_{ij}^k}| \tag{12}$$

where c_k $(k = 1, 2, ..., m)$ is the unit cost of adjusting preferences by decision maker E_k. Therefore, the following Nash stability based minimum cost inverse graph model was constructed:

$$\begin{cases} \min \sum_{k=1}^{m} \sum_{i=1}^{h-1} \sum_{j=i+1}^{h} c_k \cdot |a_{ij}^k - \overline{a_{ij}^k}| \\ s.t. \begin{cases} \overline{pv_i^k} = \frac{2}{h^2 - h} \sum_{j=1, j \neq i}^{h} \overline{a_{ij}^k}, \ k \in M; \ i \in H & (a) \\ \overline{pv_t^k} - \overline{pv_i^k} < Z \cdot x_{ti}^k, \ k \in M; s_i \in R^k(s_t) & (b) \\ \overline{pv_t^k} - \overline{pv_i^k} \geq Z \cdot (x_{ti}^k - 1), \ k \in M; s_i \in R^k(s_t) & (c) \\ \sum_{k \in M} \sum_{s_i \in R^k(s_t)} x_{ti}^k = \sum_{k \in M} \| R^k(s_t) \| & (d) \\ CL(\overline{A^k}) = 1 - \frac{4}{h(h-1)(h-2)} \sum_{i,j,z=1; i<j<z}^{n} |\overline{a_{ij}^k} + \overline{a_{jz}^k} - \overline{a_{iz}^k} - 0.5| \geq \alpha, \ k \in M & (e) \\ \overline{a_{ij}^k} + \overline{a_{ji}^k} = 1, \ k \in M; i, j \in H & (f) \\ \overline{a_{ij}^k} \in [0,1], \ k \in M; i, j \in H & (g) \\ x_{ti}^k \in \{0,1\}, \ k \in M; s_i \in R^k(s_t) & (h) \end{cases} \end{cases} \tag{13}$$

In Model (13), $\overline{a_{ij}^k}$ $(k \in M; \ i, j \in H)$ are the decision variables. **Theorem 1** transforms Model (13) into a 0-1 mixed linear programming model.

Theorem 1: By introducing the new variables $b_{ij}^k \in [0,1]$ and $d_{ijz}^k \in [0,1.5]$, the non-linear programming model (13) is equivalently transformed into the following 0-1 mixed linear programming model:

$$\begin{cases} \min \sum_{k=1}^{m} \sum_{i=1}^{h-1} \sum_{j=i+1}^{h} c_k \cdot b_{ij}^k \\ s.t. \begin{cases} a_{ij}^k - \overline{a_{ij}^k} \leq b_{ij}^k, \ k \in M; \ i, j \in H; \ i < j & (a) \\ -a_{ij}^k + \overline{a_{ij}^k} \leq b_{ij}^k, \ k \in M; \ i, j \in H; \ i < j & (b) \\ \overline{pv_i^k} = \frac{2}{h^2 - h} \sum_{j=1, j \neq i}^{h} \overline{a_{ij}^k}, \ k \in M; \ i \in H & (c) \\ \overline{pv_t^k} - \overline{pv_i^k} < Z \cdot x_{ti}^k, \ k \in M; s_i \in R^k(s_t) & (d) \\ \overline{pv_t^k} - \overline{pv_i^k} \geq Z \cdot (x_{ti}^k - 1), \ k \in M; s_i \in R^k(s_t) & (e) \\ \sum_{k \in M} \sum_{s_i \in R^k(s_t)} x_{ti}^k = \sum_{k \in M} \| R^k(s_t) \| & (f) \\ CL(\overline{A^k}) = 1 - \frac{4}{h(h-1)(h-2)} \sum_{i,j,z=1; i<j<z}^{h} d_{ijz}^k \geq \alpha, \ k \in M & (g) \\ \overline{a_{ij}^k} + \overline{a_{jz}^k} - \overline{a_{iz}^k} - 0.5 \leq d_{ijz}^k, \ k \in M; \ i, j \in H; \ i < j < z & (h) \\ -\overline{a_{ij}^k} - \overline{a_{jz}^k} + \overline{a_{iz}^k} + 0.5 \leq d_{ijz}^k, \ k \in M; \ i, j \in H; \ i < j < z & (i) \\ \overline{a_{ij}^k} + \overline{a_{ji}^k} = 1, \ k \in M; i, j \in H & (j) \\ \overline{a_{ij}^k} \in [0,1], \ k \in M; i, j \in H & (k) \\ b_{ij}^k \in [0,1], \ k \in M; \ i, j \in H; \ i < j & (l) \\ d_{ijz}^k \in [0,1.5], \ k \in M; \ i, j \in H; \ i < j < z & (m) \\ x_{ti}^k \in \{0,1\}, \ k \in M; s_i \in R^k(s_t) & (n) \end{cases} \end{cases} \tag{14}$$

The proof of Theorem 1 is in the Appendix.

(2) Minimum cost inverse graph model based on GMR stability

Here, GMR stability is considered when achieving the desired solution in the NPCD technology transfer conflict. In other words, from Lemma 3, the adjusted additive preference relations $\{\overline{A^1}, \overline{A^2}, ..., \overline{A^m}\}$ should satisfy the GMR stability conditions, and for every $s_i \in R^{k,+}(s_t)$, there exists an $s_j \in R^{M-\{k\}}(s_i)$ such that $\overline{pv_j^k} \leq \overline{pv_t^k}$. Moreover, the consistency level of $\overline{A^k}$ ($k \in M$) should be acceptable.

Naturally, as before, the mediation cost between $\{A^1, A^2, ..., A^m\}$ and $\{\overline{A^1}, \overline{A^2}, ..., \overline{A^m}\}$ must be minimized: $\min \sum_{k=1}^{m} \sum_{i=1}^{h-1} \sum_{j=i+1}^{h} c_k \cdot |a_{ij}^k - \overline{a_{ij}^k}|$. Therefore, similar to the construction of Model (13), the following GMR stability-based minimum cost inverse graph model is constructed to achieve the desired solution s_t:

$$\begin{cases} \min \sum_{k=1}^{m} \sum_{i=1}^{h-1} \sum_{j=i+1}^{h} c_k \cdot |a_{ij}^k - \overline{a_{ij}^k}| \\ s.t. \begin{cases} x_{ti}^k = \begin{cases} 1, & \overline{pv_t^k} \geq \overline{pv_i^k} \\ 0, & \overline{pv_t^k} < \overline{pv_i^k} \end{cases}, \ k \in M; s_i \in \bar{R}^k(s_t) & (a) \\ y_{tij}^k = \begin{cases} 1, & \overline{pv_t^k} \geq \overline{pv_i^k} \\ 0, & \overline{pv_t^k} < \overline{pv_i^k}, \ \overline{pv_t^k} < \overline{pv_j^k} \\ 1, & \overline{pv_t^k} < \overline{pv_i^k}, \ \overline{pv_t^k} \geq \overline{pv_j^k} \end{cases}, \ k \in M; s_i \in \bar{\bar{R}}^k(s_t); \ s_j \in R^{M-\{k\}}(s_i) & (b) \\ z_{ti}^k = \begin{cases} 1, & \sum_{s_j \in R^{M-k}(s_i)} y_{tij}^k \geq 1 \\ 0, & \sum_{s_j \in R^{M-k}(s_i)} y_{tij}^k = 0 \end{cases}, \ k \in M; s_i \in \bar{\bar{R}}^k(s_t) & (c) \\ \sum_{k \in M} \left(\sum_{s_i \in \bar{R}^k(s_t)} x_{ti}^k + \sum_{s_i \in \bar{\bar{R}}^k(s_t)} z_{ti}^k \right) = \sum_{k \in M} \| R^k(s_t) \| & (d) \\ CL(\overline{A^k}) = 1 - \frac{4}{h(h-1)(h-2)} \sum_{i,j,z=1; i<j<z}^{n} |\overline{a_{ij}^k} + \overline{a_{jz}^k} - \overline{a_{iz}^k} - 0.5| \geq \alpha, \ k \in M & (e) \\ \overline{pv_i^k} = \frac{2}{h^2 - h} \sum_{j=1, j \neq i}^{h} \overline{a_{ij}^k}, \ k \in M; \ i \in H & (f) \\ \overline{a_{ij}^k} + \overline{a_{ji}^k} = 1, \ k \in M; i, j \in H & (g) \\ \overline{a_{ij}^k} \in [0,1], \ k \in M; i, j \in H & (h) \end{cases} \end{cases} \tag{15}$$

In Model (15), $\overline{a_{ij}^k}$ $(k \in M; \ i, j \in H)$ are decision variables.

Theorem 2: Introducing new variables $b_{ij}^k \in [0,1]$, $d_{ijz}^k \in [0,1.5]$, $w_{ij}^k \in \{0,1\}$, and $u_{ij}^k \in \{0,1\}$. Model (15) can be converted into the following 0-1 mixed linear programming model:

$$\begin{cases} \min \sum_{k=1}^{m} \sum_{i=1}^{h-1} \sum_{j=i+1}^{h} c_k \cdot b_{ij}^k \\ s.t. \begin{cases} a_{ij}^k - \overline{a_{ij}^k} \leq b_{ij}^k, \ k \in M; \ i, j \in H; \ i < j & (a) \\ -a_{ij}^k + \overline{a_{ij}^k} \leq b_{ij}^k, \ k \in M; \ i, j \in H; \ i < j & (b) \\ \overline{pv_t^k} - \overline{pv_i^k} < Z \cdot x_{ti}^k, \ k \in M; s_i \in \bar{R}^k(s_t) & (c) \\ \overline{pv_t^k} - \overline{pv_i^k} \geq Z \cdot (x_{ti}^k - 1), \ k \in M; s_i \in \bar{R}^k(s_t) & (d) \\ \overline{pv_t^k} - \overline{pv_i^k} < Z \cdot w_{ti}^k, \ k \in M; s_i \in \bar{\bar{R}}^k(s_t) & (e) \\ \overline{pv_t^k} - \overline{pv_i^k} \geq Z \cdot (w_{ti}^k - 1), \ k \in M; s_i \in \bar{\bar{R}}^k(s_t) & (f) \\ \overline{pv_t^k} - \overline{pv_j^k} < Z \cdot u_{tj}^k, \ k \in M; s_i \in \bar{\bar{R}}^k(s_t); \ s_j \in R^{M-\{k\}}(s_i) & (g) \\ \overline{pv_t^k} - \overline{pv_j^k} \geq Z \cdot (u_{tj}^k - 1), \ k \in M; s_i \in \bar{\bar{R}}^k(s_t); \ s_j \in R^{M-\{k\}}(s_i) & (h) \\ w_{ti}^k + u_{tj}^k - 0.5 < Z \cdot y_{tij}^k, \ k \in M; s_i \in \bar{\bar{R}}^k(s_t); \ s_j \in R^{M-\{k\}}(s_i) & (i) \\ w_{ti}^k + u_{tj}^k - 0.5 > Z \cdot (y_{tij}^k - 1), \ k \in M; s_i \in \bar{\bar{R}}^k(s_t); \ s_j \in R^{M-\{k\}}(s_i) & (j) \\ \sum_{s_j \in R^{M-k}(s_i)} y_{tij}^k - 0.5 < Z \cdot z_{ti}^k, \ k \in M; s_i \in \bar{\bar{R}}^k(s_t) & (q) \\ \sum_{s_j \in R^{M-k}(s_i)} y_{tij}^k - 0.5 \geq Z \cdot (z_{ti}^k - 1), \ k \in M; s_i \in \bar{\bar{R}}^k(s_t) & (l) \\ \sum_{k \in M} \left(\sum_{s_i \in \bar{R}^k(s_t)} x_{ti}^k + \sum_{s_i \in \bar{\bar{R}}^k(s_t)} z_{ti}^k \right) = \sum_{k \in M} \| R^k(s_t) \| & (m) \\ CL(\overline{A^k}) = 1 - \frac{4}{h(h-1)(h-2)} \sum_{i,j,z=1; i<j<z}^{h} d_{ijz}^k \geq \alpha, \ k \in M & (n) \\ \overline{a_{ij}^k} + \overline{a_{jz}^k} - \overline{a_{iz}^k} - 0.5 \leq d_{ijz}^k, \ k \in M; \ i, j \in H; \ i < j < z & (o) \\ -\overline{a_{ij}^k} - \overline{a_{jz}^k} + \overline{a_{iz}^k} + 0.5 \leq d_{ijz}^k, \ k \in M; \ i, j \in H; \ i < j < z & (p) \\ \overline{pv_i^k} = \frac{2}{h^2 - h} \sum_{j=1, j \neq i}^{h} \overline{a_{ij}^k}, \ k \in M; \ i \in H & (q) \\ \overline{a_{ij}^k} + \overline{a_{ji}^k} = 1, \ k \in M; i, j \in H & (r) \\ \overline{a_{ij}^k}, b_{ij}^k \in [0,1], \ k \in M; i, j \in H & (s) \\ x_{ti}^k \in \{0,1\}, \ k \in M; s_i \in \bar{R}^k(s_t) & (t) \\ w_{ti}^k, u_{tj}^k, y_{tij}^k \in \{0,1\}, \ k \in M; s_i \in R^k(s_t); s_j \in R^{M-\{k\}}(s_i) & (u) \\ z_{ti}^k \in \{0,1\}, \ k \in M; s_i \in \bar{\bar{R}}^k(s_t) & (v) \\ d_{ijz}^k \in [0,1.5], \ k \in M; \ i, j \in H; \ i < j < z & (w) \end{cases} \end{cases} \tag{16}$$

The proof of Theorem 2 is similar to that of Theorem 1, and we omit its proof.

Note 1: Preference adjustment often means cost and the available resources are often limited, so minimum cost or adjustment consensus models in group decision-making have been developed (e.g., [56-59]). The basic idea of behind objective functions of the minimum cost inverse graph models comes from minimum cost consensus models [57]. Recently, several objective functions based on different cost aggregation criteria (total cost, amplitude, maximum, and variance) have been designed within an inverse graph model framework [41]. Therefore, using these objective functions to improve the proposed method would be interesting.

Note 2: (1) In Model (16), α is the parameter, and $\{\overline{a_{ij}^k},\ \overline{pv_t^k},\ b_{ij}^k,\ x_{ti}^k,\ w_{ti}^k,\ u_{ij}^k,\ y_{tij}^k,\ z_{ti}^k,\ d_{ijz}^k\}$ are the decision variables. Let Ω be the feasible region of the model (16). (i) $\Omega \neq \phi$ under different α values. For example, when setting $\overline{a_{ij}^k} = 0.5$, we can always find suitable values for $\{\overline{pv_t^k},\ b_{ij}^k,\ x_{ti}^k,\ w_{ti}^k,\ u_{ij}^k,\ y_{tij}^k,\ z_{ti}^k,\ d_{ijz}^k\}$ that satisfy all the constraints of Model (16). (ii) The feasible region is bounded because all decision variables and the objective function of Model (16) are bounded. Thus, an optimum solution to Model (16) exists when different α values are set. In addition, with an increase in the α value, the feasible region becomes smaller, and the optimal objective function increases. (2) Model (16) may have multiple optimal solutions. Therefore, new criteria can be adopted to address this problem. For example, let A^* be the set of optimal solutions to decision variables $\{\overline{A^1}, \overline{A^2}, \ldots, \overline{A^m}\}$ of Model (16) and applying the optimization model

$$\min_{\{\overline{A^{1,*}},\ldots,\overline{A^{m,*}}\} \subset A^*} \max_k d(A^k, \overline{A^{k,*}}),$$

where $d(A^k, \overline{A^{k,*}})$ is the distance between A^k and $\overline{A^{k,*}}$, yields a unique solution. This model further minimizes the maximum adjustment distance for any decision-makers. The unique solution problem is not the focus of this study and we do not provide detailed discussions owing to space constraints.

IV. Hypothetical Application

In this section, we present a hypothetical application to illustrate the usability of the proposed graph model with a minimum cost for conflict management regarding NPCD technology-transfer disputes.

Suppose two companies (denoted A and B) jointly develop a complex product. In the product development process, Company A first mastered the core technology. Owing to its weak strength, coupled with a lack of research funding and personnel, Company B did not master the core technology. Thus, Company B requires Company A to transfer its core technologies to accelerate the development process. Company B could provide Company A with high, medium compensation or low compensation. Although the two companies cooperate in R&D, there is a competitive relationship between them; at the same time, transferring core technology affects Company A's core competitiveness. Thus, Company A is unwilling to transfer technology to protect its interests, leading to a conflict between the two companies requiring a third party to coordinate and overcome the conflict.

Thus, the proposed graph model with minimum cost is used to analyze the above technology transfer conflict between companies A and B. Specifically, the parameters are set as $\alpha = 0.85$ and $c_1 = c_2 = 1$.

(1) Modelling

(i) Identification of the decision-makers. There are two decision-makers: Company A (denoted as E_1) possesses the core technology, and Company B (E_2) requires core technology transfer.

(ii) Identification of the options of decision-makers E_1 and E_2. The options for decision-makers E_1 and E_2 are $O^1 = \{o_1^1 = \text{Transfer the technology}\}$, and $O^2 = \{o_1^2 = \text{High compensation},\ o_2^2 = \text{Medium compensation},\ o_3^2 = \text{Low compensation}\}$, respectively.

(iii) Identification of the feasible states. The feasible states involved in the technology transfer conflict are listed in **Table 1.**

Table 1: Feasible states in the technology transfer conflict

Decision-makers	Options	Feasible states							
		s_1	s_2	s_3	s_4	s_5	s_6	s_7	s_8
Company A	Transfer the technology	Y	Y	Y	Y	N	N	N	N
Company B	High compensation	Y	N	N	N	Y	N	N	N
	Medium compensation	N	Y	N	N	N	Y	N	N
	Low compensation	N	N	Y	N	N	N	Y	N

(iv) Identification of the allowable state transactions. The state transition diagrams associated with the two decision-makers E_1 and E_2 are presented in Figs. 2 and 3, respectively.

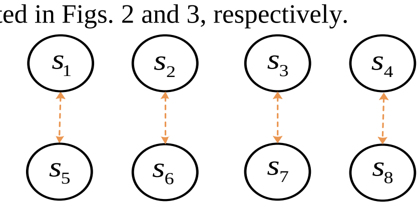


Fig. 2. The state transition diagram associated with decision-maker E_1

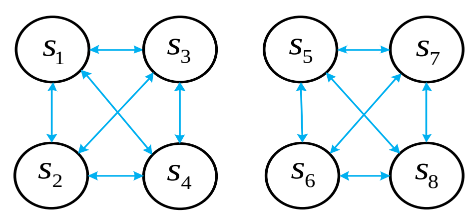


Fig. 3. The state transition diagram associated with decision-maker E_2

Meanwhile, we have that $T^1 = \{(s_1,s_5),(s_5,s_1),(s_2,s_6),(s_6,s_2),(s_3,s_7),(s_7,s_3),(s_4,s_8),(s_8,s_4)\}$, and $T^2 = \{(s_1,s_2),(s_2,s_1),(s_1,s_3),(s_3,s_1),(s_1,s_4),(s_4,s_1),(s_2,s_3),(s_3,s_2),(s_2,s_4),(s_4,s_2),(s_3,s_4),(s_4,s_3),(s_5,s_6),(s_6,s_5),(s_5,s_7),(s_7,s_5),(s_5,s_8),(s_8,s_5),(s_6,s_7),(s_7,s_6),(s_6,s_8),(s_8,s_6),(s_7,s_8),(s_8,s_7)\}$.

(v) Preference analysis. The additive preference relations over the feasible states $\{s_1, s_2, \ldots, s_8\}$ associated with decision-makers E_1 and E_2 are

$$A^1 = \begin{bmatrix} 0.5 & 0.406 & 0.4464 & 0.8499 & 0.4099 & 0.3265 & 0.2873 & 0.4747 \\ 0.594 & 0.5 & 0.6205 & 0.7694 & 0.3329 & 0.0704 & 0.4371 & 0.111 \\ 0.5536 & 0.3795 & 0.5 & 0.524 & 0.0267 & 0.1668 & 0.5825 & 0.4565 \\ 0.1501 & 0.2306 & 0.476 & 0.5 & 0.06 & 0.0856 & 0.2275 & 0.3501 \\ 0.5901 & 0.6671 & 0.9733 & 0.94 & 0.5 & 0.7997 & 0.6833 & 0.8831 \\ 0.6735 & 0.9296 & 0.8332 & 0.9144 & 0.2003 & 0.5 & 0.3268 & 0.5947 \\ 0.7127 & 0.5629 & 0.4175 & 0.7725 & 0.3167 & 0.6732 & 0.5 & 0.7679 \\ 0.5253 & 0.889 & 0.5435 & 0.6499 & 0.1169 & 0.4053 & 0.2321 & 0.5 \end{bmatrix}$$

and

$$A^2 = \begin{bmatrix} 0.5 & 0.3699 & 0.5731 & 0.2036 & 0.7401 & 0.4721 & 0.8264 & 0.5772 \\ 0.6301 & 0.5 & 0.6994 & 0.4463 & 0.3999 & 0.6764 & 0.3874 & 0.5329 \\ 0.4269 & 0.3006 & 0.5 & 0.4126 & 0.6673 & 0.7171 & 0.7181 & 0.5991 \\ 0.7964 & 0.5537 & 0.5874 & 0.5 & 0.8921 & 0.8946 & 0.8055 & 0.902 \\ 0.2599 & 0.6001 & 0.3327 & 0.1079 & 0.5 & 0.4469 & 0.3491 & 0.2463 \\ 0.5279 & 0.3236 & 0.2829 & 0.1054 & 0.5531 & 0.5 & 0.6408 & 0.1555 \\ 0.1736 & 0.6126 & 0.2819 & 0.1945 & 0.6509 & 0.3592 & 0.5 & 0.5965 \\ 0.4228 & 0.4671 & 0.4009 & 0.098 & 0.7537 & 0.8445 & 0.4035 & 0.5 \end{bmatrix}.$$

The consistency levels of A^1 and A^2 were acceptable as per Eqs. (1): $CL(A^1) = 0.851$ and $CL(A^2) = 0.852$. The preference vectors PV^1 and PV^2 are from A^1 and A^2, respectively, as per Eqs. (2) are

$$PV^1 = (0.1143,\ 0.1048,\ 0.0961,\ 0.0564,\ 0.1977,\ 0.1597,\ 0.1508,\ 0.1201)^T,$$

$$PV^2 = (0.1344,\ 0.1347,\ 0.1372,\ 0.194,\ 0.0837,\ 0.0925,\ 0.1025,\ 0.1211)^T.$$

Consequently, it follows that $PO^1 = (5,6,7,8,1,2,3,4)^T$ and $PO^2 = (4,3,2,1,8,7,6,5)^T$, which indicates that $s_5 \succ_1 s_6 \succ_1 s_7 \succ_1 s_8 \succ_1 s_1 \succ_1 s_2 \succ_1 s_3 \succ_1 s_4$ and $s_4 \succ_2 s_3 \succ_2 s_2 \succ_2 s_1 \succ_2 s_8 \succ_2 s_7 \succ_2 s_6 \succ_2 s_5$, respectively.

(2) Stability analysis via the 0-1 mixed linear approach

The 0-1 mixed linear approach was used to judge the Nash and GMR stabilities for the different feasible states involved in this technology transfer conflict. The detailed analysis process of state s_1 is described below:

From Figs. 2 and 3, it is obtained that $R^1(s_1) = \{s_5\}$ and $R^2(s_1) = \{s_2,\ s_3,\ s_4\}$, respectively. Then, applying Eq. (3) leads to $x^1_{15} = 0$, $x^2_{12} = 0$, $x^2_{13} = 0$, and $x^2_{14} = 0$. According to **Lemma 1**, the state s_1 is not Nash stable for decision-maker E_1 because of $x^1_{15} \neq \| R^1(s_1) \|$; it is not Nash stable for decision-maker E_2 since $x^2_{12} + x^2_{13} + x^2_{14} \neq \| R^2(s_1) \|$; and since $x^1_{15} + x^2_{12} + x^2_{13} + x^2_{14} \neq \| R^1(s_1) \| + \| R^2(s_1) \|$, it is not a Nash equilibrium.

Figures 2 and 3 show that $\bar{R}^1(s_1) = \phi$, $\bar{\bar{R}}^1(s_1) = \{s_5\}$, $\bar{R}^2(s_1) = \phi$, and $\bar{\bar{R}}^1(s_1) = \{s_2,\ s_3,\ s_4\}$. Eq. (5) leads to: $y^1_{156} = 0$ since $pv^1_1 < pv^1_5$ and $pv^1_1 < pv^1_6$; $y^1_{157} = 0$ since $pv^1_1 < pv^1_5$ and $pv^1_1 < pv^1_7$; $y^1_{158} = 0$ since $pv^1_1 < pv^1_5$ and $pv^1_1 < pv^1_8$; $z^1_{15} = 0$ since $y^1_{156} + y^1_{157} + y^1_{158} = 0$; $y^2_{126} = 1$ since $pv^2_1 < pv^2_2$ and $pv^2_1 > pv^2_6$; $y^2_{137} = 1$ since $pv^2_1 < pv^2_3$ and $pv^2_1 > pv^2_7$; $y^2_{148} = 1$ since $pv^2_1 < pv^2_4$ and $pv^2_1 > pv^2_8$; $z^2_{12} = 1$ since $y^2_{126} = 1$; $z^2_{13} = 1$ since $y^2_{137} = 1$; and $z^2_{14} = 1$ since $y^2_{148} = 1$. According to **Lemma 3**, the state s_1 is not GMR stable for the decision maker E_1 because $z^1_{15} = 0 \neq \| R^1(s_1) \|$; it is GMR stable for the decision maker E_2 because $z^2_{12} + z^2_{13} + z^2_{14} = 3 = \| R^2(s_1) \|$; it is not a GMR equilibrium because $z^1_{15} + z^2_{12} + z^2_{13} + z^2_{14} \neq \| R^1(s_1) \| + \| R^2(s_1) \|$.

A similar stability analysis on the other states is summarized in Table 2.

Table 2: Nash and GMR stability analysis on a set of states $\{s_1,\ s_2,\ ...,\ s_8\}$

Feasible states	E_1		E_2		Equilibria	
	Nash	GMR	Nash	GMR	Nash	GMR
s_1	N	N	N	Y	N	N
s_2	N	N	N	Y	N	N
s_3	N	N	N	Y	N	N
s_4	N	Y	Y	Y	N	Y
s_5	Y	Y	N	N	N	N
s_6	Y	Y	N	N	N	N
s_7	Y	Y	N	N	N	N
s_8	Y	Y	Y	Y	Y	Y

(3) Using the inverse approach with minimum cost

Here, state s_2 is considered the desired solution for the technology transfer conflict. Subsequently, the following two cases are considered:

Case A: Graph model based on the Nash stability concept

In this case, the state s_2 is expected to be a Nash equilibrium. Figures. 2 and 3 show $R^1(s_2) = \{s_6\}$ and $R^2(s_2) = \{s_1,\ s_3,\ s_4\}$, respectively. Taking A^1, A^2, $R^1(s_2)$ and $R^2(s_2)$ as inputs to model (14), we obtain the following adjusted additive preference relations:

$$\overline{A^1} = \begin{bmatrix} 0.5 & 0.406 & 0.4464 & 0.8499 & 0.4099 & 0.3265 & 0.2873 & 0.4747 \\ 0.594 & 0.5 & 0.6205 & 0.7694 & 0.3329 & 0.8049 & 0.4371 & 0.1802 \\ 0.5536 & 0.3795 & 0.5 & 0.524 & 0.0267 & 0.1668 & 0.5825 & 0.4565 \\ 0.1501 & 0.2306 & 0.476 & 0.5 & 0.06 & 0.0856 & 0.2275 & 0.3501 \\ 0.5901 & 0.6671 & 0.9733 & 0.94 & 0.5 & 0.7997 & 0.6833 & 0.8831 \\ 0.6735 & 0.1951 & 0.8332 & 0.9144 & 0.2003 & 0.5 & 0.3268 & 0.5947 \\ 0.7127 & 0.5629 & 0.4175 & 0.7725 & 0.3167 & 0.6732 & 0.5 & 0.7679 \\ 0.5253 & 0.8198 & 0.5435 & 0.6499 & 0.1169 & 0.4053 & 0.2321 & 0.5 \end{bmatrix}$$

and

$$\overline{A^2} = \begin{bmatrix} 0.5 & 0.3699 & 0.5731 & 0.2036 & 0.7401 & 0.4721 & 0.8264 & 0.5772 \\ 0.6301 & 0.5 & 0.6994 & 0.9828 & 0.7295 & 0.6764 & 0.5786 & 0.5329 \\ 0.4269 & 0.3006 & 0.5 & 0.4126 & 0.6673 & 0.7171 & 0.7181 & 0.5991 \\ 0.7964 & 0.0172 & 0.5874 & 0.5 & 0.8921 & 0.839 & 0.8055 & 0.8921 \\ 0.2599 & 0.2705 & 0.3327 & 0.1079 & 0.5 & 0.4469 & 0.3491 & 0.2463 \\ 0.5279 & 0.3236 & 0.2829 & 0.161 & 0.5531 & 0.5 & 0.6408 & 0.1555 \\ 0.1736 & 0.4214 & 0.2819 & 0.1945 & 0.6509 & 0.3592 & 0.5 & 0.5965 \\ 0.4228 & 0.4671 & 0.4009 & 0.1079 & 0.7537 & 0.8445 & 0.4035 & 0.5 \end{bmatrix}.$$

From Eq. (2), the following priority vectors are obtained:

$$\overline{PV^1} = (0.1143,\ 0.1335,\ 0.0961,\ 0.0564,\ 0.1977,\ 0.1335,\ 0.1508,\ 0.1176)^T$$

and $\overline{PV^2} = (0.1344,\ 0.1725,\ 0.1372,\ 0.1725,\ 0.0719,\ 0.0945,\ 0.0956,\ 0.1214)^T$.

Case B: Graph model based on the GMR stability concept

In this case, state s_2 is expected to be a GMR equilibrium. From Figures 2 and 3 show that $\bar{R}^1(s_2) = \phi$, $\bar{\bar{R}}^1(s_2) = \{s_6\}$, $\bar{R}^2(s_2) = \phi$, and $\bar{\bar{R}}^1(s_2) = \{s_1, s_3, s_4\}$, respectively. Using A^1, A^2, $\bar{R}^1(s_2)$, $\bar{\bar{R}}^1(s_2)$, $\bar{R}^2(s_2)$, and $\bar{\bar{R}}^1(s_2)$ as inputs to Model (16), we obtain the following adjusted preference relations and associated priority vectors:

$$\overline{\overline{A^1}} = \begin{bmatrix} 0.5 & 0.406 & 0.4464 & 0.8499 & 0.4099 & 0.3265 & 0.2873 & 0.4747 \\ 0.594 & 0.5 & 0.6205 & 0.7694 & 0.3329 & 0.0704 & 0.4371 & 0.3243 \\ 0.5536 & 0.3795 & 0.5 & 0.524 & 0.0267 & 0.1668 & 0.5825 & 0.4565 \\ 0.1501 & 0.2306 & 0.476 & 0.5 & 0.06 & 0.0856 & 0.2275 & 0.3501 \\ 0.5901 & 0.6671 & 0.9733 & 0.94 & 0.5 & 0.7997 & 0.6833 & 0.8831 \\ 0.6735 & 0.9296 & 0.8332 & 0.9144 & 0.2003 & 0.5 & 0.3268 & 0.5947 \\ 0.7127 & 0.5629 & 0.4175 & 0.7725 & 0.3167 & 0.6732 & 0.5 & 0.7679 \\ 0.5253 & 0.6757 & 0.5435 & 0.6499 & 0.1169 & 0.4053 & 0.2321 & 0.5 \end{bmatrix}.$$

and $\overline{\overline{A^2}} = A^2$;

$\overline{\overline{PV^1}} = (0.1143, 0.1125, 0.0961, 0.0564, 0.1977, 0.1597, 0.1508, 0.1125)^T$ and $\overline{\overline{PV^2}} = PV^2$.

V. Numerical and Comparison Analysis

This section reports a numerical and comparative analysis of the proposed graph model with minimum cost.

A. Numerical analysis

First, we analyzed how the cost of the conflict resolution approach described in Section 4 was affected by the consistency threshold, unit costs, different desired solutions, and stability concepts.

(1) The effect of the consistency threshold on the conflict resolution cost

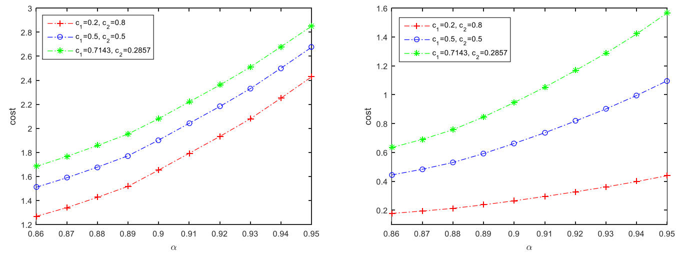
Three combinations of parameters scenarios are considered under the Nash and GMR stabilities:

(i) $\alpha = \{0.86, 0.87, ..., 0.95\}$, $\{(c_1 = 0.2, c_2 = 0.8), (c_1 = 0.5, c_2 = 0.5), (c_1 = 0.7143\ c_2 = 0.2857)\}$, and $s_t = s_1$ (i.e., the desirable solution is s_1);

(ii) $\alpha = \{0.86, 0.87, \ldots, 0.95\}$, $\{(c_1 = 0.2, c_2 = 0.8), (c_1 = 0.5, c_2 = 0.5), (c_1 = 0.7143$ $c_2 = 0.2857)\}$, and $s_t = s_2$ (i.e., the desirable solution is s_2),

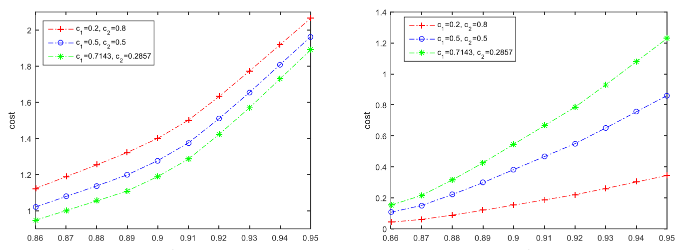
(iii) $\alpha = \{0.86, 0.87, \ldots, 0.95\}$, $\{(c_1 = 0.2, c_2 = 0.8), (c_1 = 0.5, c_2 = 0.5), (c_1 = 0.7143$ $c_2 = 0.2857)\}$, and $s_t = s_3$ (i.e., the desirable solution is s_3).

The conflict resolution costs for these three parameter combinations are shown in Figs. 4-6, respectively.



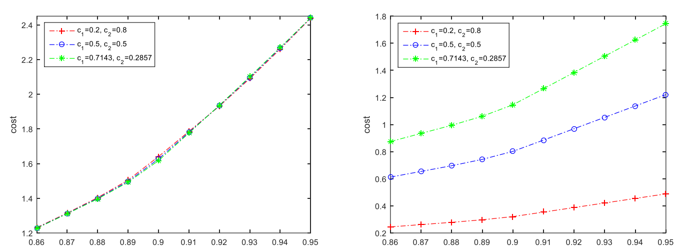
(a) Nash stability (b) GMR stability

Fig. 4: The cost for desirable state s_1 under the Nash and GMR stabilities



(a) Nash stability (b) GMR stability

Fig. 5: The cost for desirable state s_2 under the Nash and GMR stabilities



(a) Nash stability (b) GMR stability

Fig. 6: The cost for desirable state s_3 under the Nash and GMR stabilities

(2) The effect of the stability concepts on the conflict resolution cost

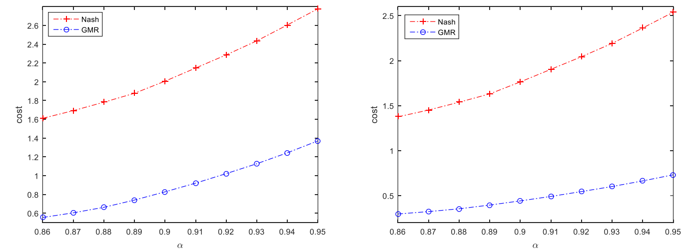
The following three situations are considered:

(i) $\alpha = \{0.86, 0.87, \ldots, 0.95\}$, $\{(c_1 = 0.625, c_2 = 0.375), (c_1 = 0.3333, c_2 = 0.6667)\}$, and $s_t = s_1$ (i.e. the desirable solution is s_1), Nash and GMR stability concepts are used;

(ii) $\alpha = \{0.86, 0.87, \ldots, 0.95\}$, $\{(c_1 = 0.625, c_2 = 0.375), (c_1 = 0.3333, c_2 = 0.6667)\}$, and $s_t = s_2$ (i.e. the desirable solution is s_2), Nash and GMR stability concepts are used;

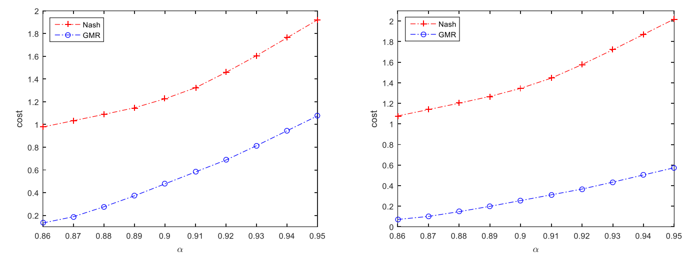
(iii) $\alpha = \{0.86, 0.87, \ldots, 0.95\}$, $\{(c_1 = 0.625, c_2 = 0.375), (c_1 = 0.3333, c_2 = 0.6667)\}$, and $s_t = s_3$ (i.e. the desirable solution is s_3), Nash and GMR stability concepts are used.

The conflict resolution costs for the three cases above are shown in Figs. 7-9, respectively.



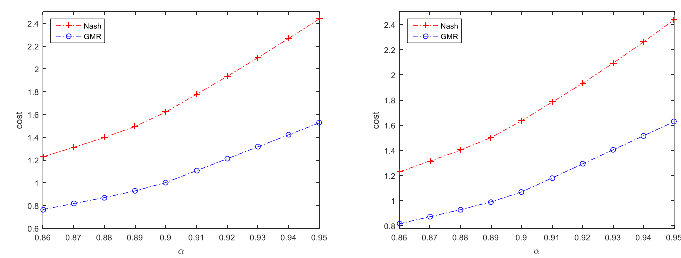
(a) $\{c_1 = 0.625,\ c_2 = 0.375\}$ (b) $\{c_1 = 0.3333,\ c_2 = 0.6667\}$

Fig. 7: The cost for desirable state s_1 under parameters $\{c_1 = 0.625,\ c_2 = 0.375\}$ and $\{c_1 = 0.3333,\ c_2 = 0.6667\}$



(a) $\{c_1 = 0.625,\ c_2 = 0.375\}$ (b) $\{c_1 = 0.3333,\ c_2 = 0.6667\}$

Fig. 8: The cost for desirable state s_2 under parameters $\{c_1 = 0.625,\ c_2 = 0.375\}$ and $\{c_1 = 0.3333,\ c_2 = 0.6667\}$



(a) $\{c_1 = 0.625,\ c_2 = 0.375\}$ (b) $\{c_1 = 0.3333,\ c_2 = 0.6667\}$

Fig. 9: The cost for desirable state s_3 under parameters $\{c_1 = 0.625,\ c_2 = 0.375\}$ and $\{c_1 = 0.3333,\ c_2 = 0.6667\}$

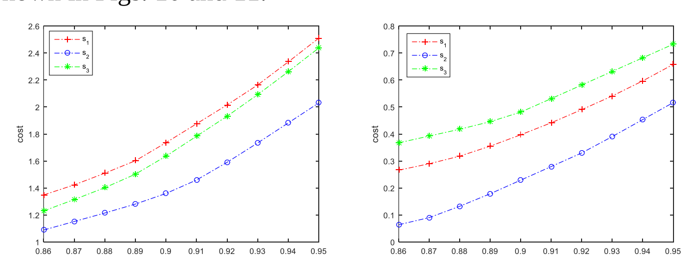
(3) The effect of the different desirable solutions on the conflict resolution cost

The following two-parameter combination scenarios under the Nash and GMR stabilities are considered:

(i) $\alpha = \{0.86,\ 0.87,\ \ldots,\ 0.95\}$, $\{c_1 = 0.3,\ c_2 = 0.7\}$, and $s_t = \{s_1,\ s_2,\ s_3\}$ (i.e. the desirable solutions are s_1, s_2, and s_3);

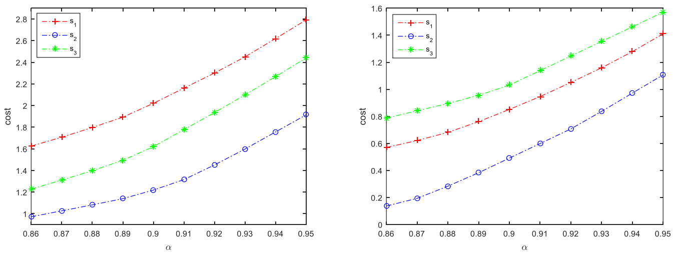
(ii) $\alpha = \{0.86,\ 0.87,\ \ldots,\ 0.95\}$, $\{c_1 = 0.6429, c_2 = 0.3571\}$, and $s_t = \{s_1,\ s_2,\ s_3\}$ (i.e. the desirable solutions are s_1, s_2, and s_3).

The conflict resolution costs for the above two scenarios are shown in Figs. 10 and 11.



Nash GMR

Fig. 10: The cost for desirable states $\{s_1, s_2, s_3\}$ under the Nash and GMR stabilities and parameters $\{c_1 = 0.3,\ c_2 = 0.7\}$



(a) Nash stability (b) GMR stability

Fig. 11: The cost for desirable states $\{s_1, s_2, s_3\}$ under the Nash and GMR stabilities and parameters $\{c_1 = 0.6429, c_2 = 0.3571\}$

Figs. 4-11 show that the conflict-resolution costs increase when the consistency threshold increases in the parameter combination scenarios considered. Figs. 7-9 show that achieving a Nash equilibrium is costlier than achieving a GMR equilibrium, which follows from the fact that every Nash equilibrium is also a GMR equilibrium, as shown by Rêgo et al. [41]. Using the Nash stability concept, Figs. 10(a) and 11(a) indicate that achieving state s_1 is costlier than achieving state s_3, while achieving state s_2 is the least costly. Using the GMR stability concept, Figs. 10(b) and 11(b) show that achieving state s_3 is costlier than achieving state s_1, while achieving state s_2 is the least costly.

B. Comparison analysis

The graph model with minimum cost for modelling the NPCD technology transfer conflict presented in this study was inspired by the advances achieved in the graph model. In the following, the proposed graph model with minimum cost is compared with existing graph models for conflict resolution. In particular, the most distinctive features of the proposed graph model with the minimum cost were identified and compared with the main characteristics of several related graph models for conflict resolution.

(1) Approach to analyze the stability within the graph model framework. There are two methods to judge stability concepts within the graph model framework in the existing literature: logic-based approaches (e.g. [3, 4, 14, 27, 28, 43, 51, 54]), and matrix representation-based approaches (e.g. [48, 52, 60]). Compared with these approaches, this study contributes with a new 0-1 mixed linear approach for judging widely used stability concepts.

(2) Inverse problem within the graph model framework. Existing graph models that address the inverse problem are mainly based on the brute-force method (e.g., [14, 27, 48]). As the name suggests, this method tests each possible preference profile for each decision maker against the desired equilibrium. Because the number of possible preference orderings can be fairly large in practice, the number of iterations required to obtain the desired equilibrium may be very large. Compared to the brute-force method, the present study contributes to an efficient 0-1 mixed linear programming method to address the inverse problem within the graph model framework. Recently, Han et al. [15] and Rêgo et al. [41] proposed optimization-based approaches to address the inverse problem within a graph model framework. The main difference between [15, 41] and our proposal is that different stability representation approaches were used.

(3) The cost to achieve the desirable solution. Existing studies on graph models mainly focus on designing methods or algorithms to specify which decision makers' preferences lead to the desired solution (e.g., [14, 27, 48]). To the best of our knowledge, the cost of a mediator or other third party influencing the course of the conflict was not considered except for the inverse graph models presented by Rêgo et al. [41], Tao et al. [46], and our proposal. The basic idea of our proposal is inspired by [41] and [46], which are all based on optimization models. Notably, there are some differences in our proposal compared with [41] and [46]: (a) The methods for measuring the cost in the objective function are different because of the different preference formats. The cost of altering preference ordering was measured based on preference reversal in [41] and [46]. In our proposal, the cost is measured based on the preference adjustment distance. (b) The constraints that ensure that a desirable solution is an equilibrium are based on different stability representation approaches. Logic- and matrix representation-based approaches were employed in [41] and [46], respectively. The 0-1 mixed linear representation approach was used in our proposal. Moreover, some constraints are utilized in our model to ensure consistency (similar to transitivity in preference orderings) of the adjusted preferences. (c) The types of optimization models are different. The optimization models presented in [41] and [46] are non-linear programming models. In our proposal, 0-1 mixed linear programming models were constructed to achieve the desired solution, which can be solved using readily available software packages (such as MATLAB and CPLEX).

Comparisons between the existing graph models and the proposed graph model with the minimum cost are summarized in Table 3.

Table 3: Comparisons of the graph model with the minimum cost and existing graph models

Graph models	**Preference formats**	**Approach for stability analysis**	**Approach to address inverse problem**	**The cost to achieve desired solution**
Bashar et al. [3, 4]	Additive preference relations	Logic-based approach	Inverse problem was not considered	Not considered
Garcia et al. [14]	Preference ordering	Logic-based approach	Brute-force method	Not considered
Han et al. [15]	Preference matrices	Matrix representation-based approach	Optimization-based approach	Not considered
Kinsara et al. [27]	Preference orderings	Logic-based approach	Improved Brute-Force method	Not considered
Kuang et al. [28]	Grey-based preference structure	Logic-based approach	Inverse problem was not considered	Not considered
Rêgo et al. [41]	Preference orderings	Logic-based approach	Optimization-based approach	The cost is minimized
Rêgo and Vieira [43]	Probabilistic Preferences	Logic-based approach	Inverse problem was not considered	Not considered
Rêgo and Vieira [44]	Probabilistic Preferences	Matrix representation-based approach	Inverse problem was not considered	Not considered
Tao et al. [46]	Preference orderings	Matrix representation-based approach	Optimization-based approach	The cost is minimized
Wang et al. [48]	Preference matrices	Matrix representation-based approach	Brute-force method	Not considered
Wu et al. [51]	Incomplete additive preference relations	Logic-based approach	Inverse problem was not considered	Not considered
Xu et al. [52]	Preference orderings	Matrix representation-	Inverse problem was not	Not considered

		based approach	considered	
Yu et al. [54]	Hybrid preference structure	Logic-based approach	Inverse problem was not considered	Not considered
Zhao et al. [60]	Preference orderings	Matrix representation-based approach	Inverse problem was not considered	Not considered
The graph model with minimum cost	**Additive preference relations**	**0-1 mixed linear representation approach**	**0-1 mixed linear programming model**	**The cost is minimized**

VI. Conclusion

This study investigates the NPCD technology transfer conflict, with preferences over feasible states assumed to be modelled using additive preference relations. This study designed a graph model with minimum cost to achieve the desired solution for conflict resolution in NPCD technology transfer. Specifically, a 0-1 mixed linear approach was devised to analyze the widely used Nash and GMR stability concepts. Subsequently, two 0-1 mixed linear optimization models with minimum mediation costs were constructed for the mediator to guide the technology transfer conflict resolution process of the NPCD to achieve the desired solution.

The graph model with minimum cost was validated using a case study, numerical analysis, and comparison analysis. Compared with existing relevant works, this study provides a new and more effective method for conflict resolution, as well as novel theoretical insights and practical implications for improving cooperation efficiency in complex product collaborative development.

Moreover, there are three directions for future research:

(1) Owing to space limitations, we only provide a solution to the Nash and GMR stability concepts in the inverse graph model at minimum cost. In future research, it would be interesting to consider other stability concepts such as SMR [20], SEQ [13], and SSEQ [42].

(2) In the future, we plan to apply machine learning techniques to estimate the preferences of decision-makers from historical data within the graph model for conflict resolution.

(3) Mediator bias may exist in the conflict mediation process. Moreover, decision makers may adopt strategic manipulation behaviours to pursue their own interests. Therefore, considering and managing mediator bias and strategic manipulation behaviours to improve conflict resolution is a promising research direction.

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Appendix

Proof of Lemma 1:

Proof of (i):

Sufficiency: Because state s_t is Nash stable for decision maker E_k, from Definition 2, it is $R^{k,+}(s_t)=\phi$. Thus, $pv_t^k \geq pv_i^k$ (i.e. $s_t \succeq_k s_i$) holds for all states $s_i \in R^k(s_t)$. According to Eq. (3), it follows that the $x_{ti}^k = 1$ for all states is $s_i \in R^k(s_t)$ and therefore, $\sum_{s_i \in R^k(s_t)} x_{ti}^k = \| R^k(s_t) \|$.

Necessity: Because $\sum_{s_i \in R^k(s_t)} x_{ti}^k = \| R^k(s_t) \|$, it follows that $x_{ti}^k = 1$ for all states $s_i \in R^k(s_t)$. Moreover, $pv_t^k \ge pv_i^k$ (i.e. $s_t \succeq_k s_i$) holds for all states $s_i \in R^k(s_t)$. As a result, by Definition 2, the state s_t is Nash stable for the decision-maker E_k.

Proof of (ii):

Sufficiency: According to (i), $\sum_{s_i \in R^k(s_t)} x_{ti}^k = \| R^k(s_t) \|$ holds for all decision-makers because the state s_t is the global Nash stable. Thus, $\sum_{k=1}^{m} \sum_{s_i \in R^k(s_t)} x_{ti}^k = \sum_{k=1}^{m} \| R^k(s_t) \|$.

Necessity: Because $\sum_{k=1}^{m} \sum_{s_i \in R^k(s_t)} x_{ti}^k = \sum_{k=1}^{m} \| R^k(s_t) \|$, the equality $\sum_{s_i \in R^k(s_t)} x_{ti}^k = \| R^k(s_t) \|$ holds for all decision-makers. According to (i), s_t is globally Nash stable.

Proof of Lemma 2:

The following three cases are considered:

Case A: $pv_t^k > pv_i^k$. In this case, (a) and (c) ensure that $x_{ti}^k = 1$, (b) and (c) guarantee that $x_{ti}^k = 1 \text{ or } 0$. Thus, it follows that $x_{ti}^k = 1$ according to (a), (b) and (c).

Case B: $pv_t^k = pv_i^k$. In this case, (a) and (c) guarantee that $x_{ti}^k = 1$, (b) and (c) ensure that $x_{ti}^k = 1 \text{ or } 0$. So, (a), (b) and (c) guarantee that $x_{ti}^k = 1$.

Case C: $pv_t^k < pv_i^k$. In this case, (a) and (c) ensure that $x_{ti}^k = 1 \text{ or } 0$, and (b) and (c) guarantee that $x_{ti}^k = 0$. Thus, it follows that $x_{ti}^k = 0$ according to (a), (b) and (c).

Therefore, $x_{ti}^k \quad (s_i \in R^k(s_t))$ can be determined using constraints (a), (b), and (c).

Proof of Lemma 3:

Proof of (i):

(a) Sufficiency. Because state s_t is GMR stable for decision-maker E_k, one of the following two cases must be verified.

Case A: $pv_t^k \ge pv_i^k$ for all $s_i \in \bar{R}^k(s_t)$. In this case, it follows that $x_{ti}^k = 1$ and $\sum_{s_i \in \bar{R}^k(s_t)} x_{ti}^k = \| \bar{R}^k(s_t) \|$.

Case B: The following conditions hold: (a) $pv_t^k \ge pv_i^k$ ($s_i \in \bar{\bar{R}}^k(s_t)$) or (b) there exists a state s_j ($s_i \in \bar{\bar{R}}^k(s_t)$ and $s_j \in R^{M-\{k\}}(s_i)$) such that $pv_t^k < pv_i^k$ and $pv_t^k \ge pv_j^k$. If (a), it follows that $\sum_{s_j \in R^{M-\{k\}}(s_i)} y_{tij}^k = \| R^{M-\{k\}}(s_i) \|$. If (b), In this case, it follows that $\sum_{s_j \in R^{M-\{k\}}(s_i)} y_{tij}^k \ge 1$. In both (a) and (b), it follows that $\sum_{s_j \in R^{M-\{k\}}(s_i)} y_{tij}^k \ge 1$. In addition, it follows that $z_{ti}^k = 1$ for $s_i \in \bar{\bar{R}}^k(s_t)$ and $\sum_{s_i \in \bar{\bar{R}}^k(s_t)} z_{ti}^k = \| \bar{\bar{R}}^k(s_t) \|$.

Thus, it follows that $\sum_{s_i \in \bar{R}^k(s_t)} x_{ti}^k + \sum_{s_i \in \bar{\bar{R}}^k(s_t)} z_{ti}^k = \| \bar{R}^k(s_t) \| + \| \bar{\bar{R}}^k(s_t) \| = \| R^k(s_t) \|$ for both Cases A and B.

(b) Necessity. Since $\sum_{s_i \in \bar{R}^k(s_t)} x_{ti}^k + \sum_{s_i \in \bar{\bar{R}}^k(s_t)} z_{ti}^k = \| R^k(s_t) \|$, it follows that $\sum_{s_i \in \bar{R}^k(s_t)} x_{ti}^k = \| \bar{R}^k(s_t) \|$ and $\sum_{s_i \in \bar{\bar{R}}^k(s_t)} z_{ti}^k = \| \bar{\bar{R}}^k(s_t) \|$. The following cases are considered:

Case A: $\sum_{s_i \in \bar{R}^k(s_t)} x_{ti}^k = \| \bar{R}^k(s_t) \|$. In this case, $x_{ti}^k = 1$ and $pv_t^k \ge pv_i^k$ for all $s_i \in \bar{R}^k(s_t)$. So, the decision-maker E_k will not move to state s_i if $s_i \in \bar{R}^k(s_t)$.

Case B: $\sum_{s_i \in \bar{\bar{R}}^k(s_t)} z_{ti}^k = \| \bar{\bar{R}}^k(s_t) \|$. In this case, (a) $pv_t^k \ge pv_i^k$ or (b) there exists a state s_j ($s_i \in \bar{\bar{R}}^k(s_t)$ and $s_j \in R^{M-\{k\}}(s_i)$) such that $pv_t^k < pv_i^k$ and $pv_t^k \ge pv_j^k$. As a result, the decision-maker E_k will also not move to state s_i if $s_i \in \bar{\bar{R}}^k(s_t)$.

According to the above analysis, Definition 3 implies that the state s_t is GMR stable for the decision-maker E_k.

This completes the proof of point (i). The proof of (ii) is omitted because it can be obtained directly from (i).

Proof of Lemma 4:

Proof: (i) The following three cases are considered.

Case A: $pv_t^k > pv_i^k$. In this case, (a) and (c) ensure that $x_{ti}^k = 1$, (b) and (c) guarantee that $x_{ti}^k = 1 \text{ or } 0$, so it follows that $x_{ti}^k = 1$ according to (a), (b) and (c).

Case B: $pv_t^k = pv_i^k$. In this case, (a) and (c) ensure that $x_{ti}^k = 1$, (b) and (c) guarantee that $x_{ti}^k = 1 \text{ or } 0$, so it is $x_{ti}^k = 1$ according to (a), (b) and (c).

Case C: $pv_t^k < pv_i^k$. In this case, (a) and (c) ensure that $x_{ti}^k = 1 \text{ or } 0$, (b) and (c) guarantee that $x_{ti}^k = 1$, so we have that $x_{ti}^k = 1$ according to (a), (b) and (c).

Therefore, $x_{ti}^k \quad (s_i \in \bar{R}^k(s_t))$ can be determined using constraints (a), (b) and (c).

(ii) (a) and (b) ensure that $w_{ti}^k = 1$ if $pv_t^k \ge pv_i^k$, and $w_{ti}^k = 0$ if $pv_t^k < pv_i^k$. (c) and (d) ensure $u_{tj}^k = 1$ if $pv_t^k \ge pv_j^k$, and $u_{tj}^k = 0$ if $pv_t^k < pv_j^k$; (e) and (g) ensure $y_{tij}^k = 1$ if (1) $w_{ti}^k = 1$ and $u_{tj}^k = 0$, (2) $w_{ti}^k = 0$ and $u_{tj}^k = 1$, or (3) $w_{ti}^k = 1$ and $u_{tj}^k = 1$, and $y_{tij}^k = 0$ if $w_{ti}^k = 0$ and $u_{tj}^k = 0$. This completes the proof of (ii).

(iii) (a) and (b) guarantee $z_{ti}^k = 1$ only when $\sum_{s_j \in R^{M-\{k\}}(s_i)} y_{tij}^k \ge 1$; otherwise, $z_{ti}^k = 0$. This completes the proof of (iii).

Proof of Theorem 1:

Proof: Based on constraints (a) and (b), it follows that $| a_{ij}^k - \overline{a_{ij}^k} | \le b_{ij}^k$ in Model (14), and thus the optimal value of the objective function is obtained only when $| a_{ij}^k - \overline{a_{ij}^k} | = b_{ij}^k$. Moreover, according to constraints (h) and (i), it follows that $| \overline{a_{ij}^k} + \overline{a_{jz}^k} - \overline{a_{iz}^k} - 0.5 | \le d_{ijz}^k$. Constraint (g) implies that

$$1 - \frac{4}{h(h-1)(h-2)} \sum_{i,j,z=1;i<j<z}^{h} | \overline{a_{ij}^k} + \overline{a_{jz}^k} - \overline{a_{iz}^k} - 0.5 | \ge 1 - \frac{4}{h(h-1)(h-2)} \sum_{i,j,z=1;i<j<z}^{h} d_{ijz}^k \ge \alpha .$$

Thus, Model (13) can be equivalently transformed into the 0-1 mixed linear programming Model (14).

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