Concept of Sustainable Supply Chain Management Using Multi-agent System: Negotiation by Linear Physical Programming

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Abstract. Industry and academia are both making efforts to realize a sustainable society; an important part of these efforts is to ensure the sustainability of the supply chains that support our daily life. Sustainable supply chains are more complex than traditional supply chains, and they involve a combination of multiple issues. Multiple plans must be used to deal with these issues. However, these plans often conflict with each other. To manage a sustainable supply chain, an integrated approach is needed to operate multiple plans for multiple issues.

This paper introduces a research concept for integrated sustainable supply chain management using a multi-agent system. An agent executing a plan for an issue autonomously negotiates with other agents and avoids conflicts. Linear physical programming used for negotiation balances agents' utility and ensures that all plans function well. Through this research, we provide an example of the simultaneous operation of multiple plans in a sustainable supply chain, aiming at the social implementation of sustainable supply chains.

Keywords: Research concept · Decision making · Linear physical programming · Negotiation process

1 Introduction

In recent years, concerns about the depletion of natural resources and the emergence of environmental problems have heightened the need for sustainable production and consumption. In particular, the supply chain (SC), which is the basis of production and consumption, needs to become a sustainable supply chain (SSC) that is economically viable as a business while taking the environment into consideration.

In a conventional linear SC, the amount consumed is directly related to the amount sold, resulting in a trade-off between the environment and the economy. Therefore, a typical example of SSC is the closed-loop supply chain (CLSC), which adds the process of collecting and reusing used products to the conventional SC. However, to operate the CLSC sustainably, it is necessary to deal with the problems associated with the uncertain recovery of used products, in addition to the demand fluctuations and other problems

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associated with conventional SCs. This means that sustainable supply chain management (SSCM) requires more problem-solving capabilities than conventional SCM.

SSCM has been an active field of research. Ghadimi et al. [1] studied the supplier selection and order allocation problem using multi-agent technology to make the supply chain sustainable. Takahashi et al. [2] proposed an adaptive pull strategy that changes the manufacturing and remanufacturing speed according to various inventory levels as a management method for SSCs. Other areas of research include the location routing problem for SSCs [3] and dynamic pricing of products according to reuse rates [4]. Thus, previous studies have focused on one phase of SSCs, such as maintenance, recovery, and remanufacturing, in addition to parts supply, manufacturing, transportation, and sales. However, when SSC is actually implemented, each of these issues is not independent of the other, and it is necessary to deal with problems that occur in combination. Goltsos et al. [5] argued that it was necessary to synchronize and coordinate the three planning processes of forecasting, collection, and inventory and production control to deal with the problems that arise in SSC. To implement SSC and realize a sustainable society, we believe that an integrated SSCM (ISSCM) is necessary to synchronize and link not only the three above-mentioned processes but also the SSCMs that are being developed separately at each stage.

Synchronization and coordination of multiple SSCMs is not a simple task. For example, changing the manufacturing or remanufacturing speed will change the transportation requirements. Changing the pricing of a product will affect the profit margins of all members of the SC. Since each SSCM is intended to solve a specific problem and the modeling assumes that other elements will be omitted to some extent, synchronization and coordination can cause various conflicts. SSCMs that ignore conflicts will find it difficult to deal with even a single issue, let alone multiple issues, leading to worsening environmental impacts and economic viability, as well as loss of sustainability. If the weight of each SSCM is unbalanced, the burden may fall on certain members, and the SC may fail. Therefore, a conflict-resolving negotiation process is needed to effectively synchronize and coordinate multiple SSCMs for multiple issues.

This paper introduces the research concept of ISSCM using a multi-agent system. The manufacturers, retailers, collectors, etc., that make up the SSC are considered as agents, each with its own utility and freely changeable plan. Each agent makes planning decisions through inter-agent negotiation so that utility is not significantly impaired. We believe that using this system to provide an example in which all agents execute a plan to solve a problem while maintaining a certain level of utility will support the social implementation of SSC by real decision makers.

2 SSC Model Construction Using a Multi-agent System

2.1 Effectiveness of Multi-agent System for ISSCM

A multi-agent system (MAS) is an autonomous decentralized system in which multiple agents are aware of their own environment and make decisions and act accordingly. In general, SCM is an approach that comprehensively manages all processes from the procurement of raw materials to the provision of products and services to customers, aiming to improve efficiency, and, therefore, MAS and SCM are not, at first glance, compatible with each other. However, several studies have suggested combining SCM with MAS. Fox et al. [6] described an integrated SCM (ISCM) architecture that divides the operational level of SCM functions from the strategic level and handles each function in an integrated, rather than an independent, manner. Each function that makes up ISCM is executed by an agent, which makes decisions through coordination with other related agents. Fox et al. assumed an SC in which multiple functions interactively influence each other and employed MAS, an autonomous decentralized system, to manage them. Lou et al. [7] adopted MAS for agile SCM, which involves rapid reconfiguration and adjustment to the SC itself, rather than the traditional line-type SC. MAS, which is more flexible and adaptable than centralized systems, is suitable for agile SCM, which aims to keep changing the constituent companies and scale quickly and appropriately to the environment.

Let us consider the characteristics of ISSCM. SSCs raise more issues than regular SCs because of factors such as recovery and remanufacturing. Since the ISSCM targeted in this study aims to deal with multiple issues at the same time, rather than a single one, it necessarily has multiple functions, requiring coordination between functions. In addition to demand forecasting, SSC involves the uncertainty of used product recovery, which requires flexibility and adaptability when considering how to deal with non-stationary demand and recovery. Therefore, this study will implement ISSCM combined with MAS.

2.2 SSC Model Construction

The modeling of SSCs subject to ISSCM is divided into two major steps (see Fig. 1).

Step 1: Definition of the subject of the material flow

Will new and remanufactured products be distinguished; how many echelon inventories will be assumed; and in what detail will attributes such as product quality be handled? In this way, the definition of the material flow for the target SSC is determined. This allows us to design a simulation model of the material flow.

Step 2: Determination of the subject in the information flow.

An agent is defined as an entity that receives information and manages the material flow. Each agent has the ability to recognize the state of its own environment and the simulation model and change the material flow it manages accordingly. For example, when an agent managing remanufacturers becomes aware of a high inventory of recovered products, it decides to increase the number of remanufactures so as to reduce the inventory of recovered products and increase profits. However, if the retailer receiving the remanufactured product has a large inventory, a conflict arises with the agent managing the retailer. Negotiations among agents are conducted to avoid such conflicts and to make each agent's management functions work effectively.

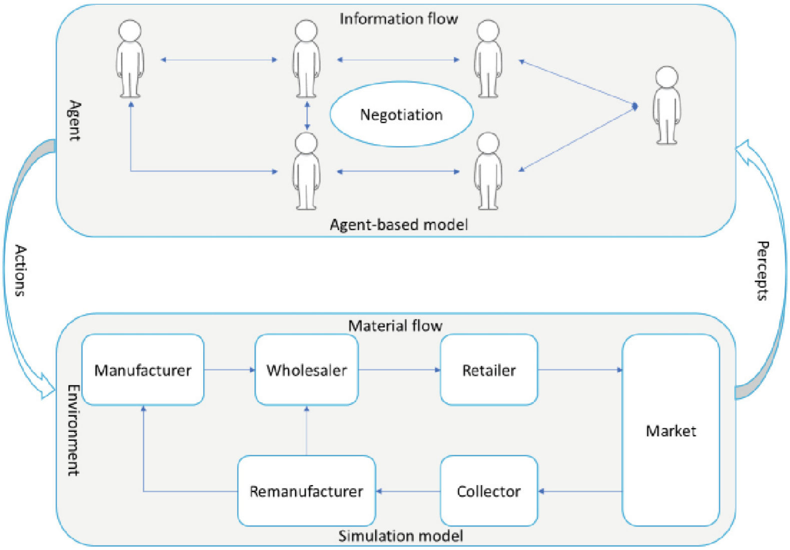

Fig. 1. Conceptual diagram of SSC model for ISSCM

3 Agent Decision-Making Process Through Negotiation

3.1 Suriawase Process

One of the negotiated decision-making methods involving multiple negotiation participants with different levels of utility is the Suriawase process [8]. In the Suriawase process, each negotiator presents their best plan as an initial proposal, and through repeated negotiations and goal reviews, a common alternative is developed that satisfies all negotiators. The procedure to be followed is shown below.

Step 1: Each negotiator presents an initial proposal.
Step 2: All negotiators share goals.
Step 3: A solution is created from the given goals.
Step 4: If the solution in Step 3 does not satisfy all negotiators, each participant revises the goals and returns to Step 2.
Step 5: A final alternative is determined.

There are two ways to share goals for alternative development. One is Point-based Design (PD), which presents only one reference value for the objective function to be pursued by the negotiation participants. The other is Preference Set-based Design (PSD), which presents multiple reference values as a set according to the preference level. This study's negotiation design follows the model of a PSD to be conducted between agents by using the following method.

3.2 Linear Physical Programming

In the Suriawase process, all participants negotiate with each other by presenting target values for their own objective functions. For successful negotiation, we focus on multi-objective optimization methods where the target value is given by each objective function. Goal programming (GP) [9] is known as a multi-objective optimization method. GP corresponds to PD in the Suriawase process. GP defines priorities for each objective and sets weighting coefficients. The optimal solution is obtained by calculating the separation of each objective from the ideal, considering the weighting coefficients, and minimizing the sum. However, it is difficult to set appropriate weighting coefficients in GP. For example, the optimal setting of the weighting coefficients for out-of-stock risk and excess inventory risk in SCM changes constantly depending on the situation. To address this weighting coefficient problem, this study uses linear physical programming (LPP) [10] as a negotiation method between agents. LPP is equivalent to PSD. LPP is characterized by its ability to derive weighted coefficients algorithmically by providing multiple target values and a preference range for each objective. This allows agents to derive weighting coefficients autonomously during negotiations.

Figure 2 shows an example of transforming an objective function for a given objective into a preference function by setting a preference range with multiple target values. LPP aims to minimize the sum of the preference functions for each objective that shows the difference from the ideal. Another feature of LPP is the OVO (One vs. Others) rule. According to this rule, it is better for all preference functions to be equal than for one objective preference function to worsen and all others to improve. This ensures that the obtained solution is balanced by the preference function among all objectives. That is, by making the LPP objective the objective function of each negotiation participant, an alternative can be developed that satisfies all negotiators.

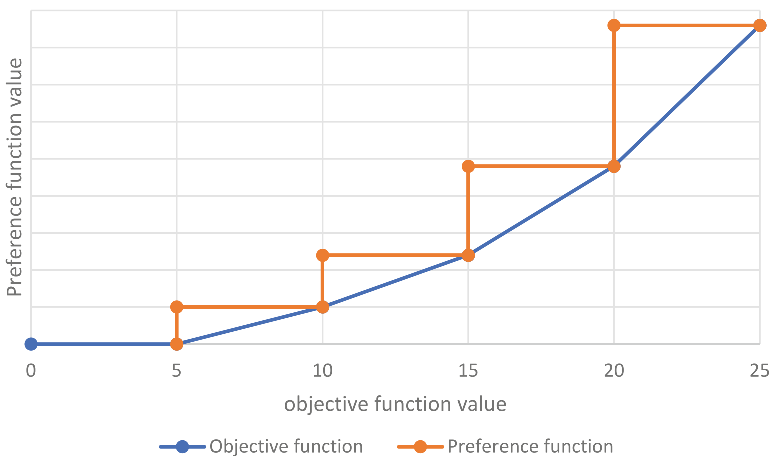

Fig. 2. Example of transforming objective function into preference function

3.3 Decision-Making Flow of Each Agent

Figure 3 shows the decision-making flow of each agent. Each agent perceives the information (e.g., amount of inventory, expected deliveries, etc.) of the entities (manufacturers, remanufacturers, etc.) in the material flow that it manages. On this basis, it formulates an optimal plan that maximizes its own utility and shares the optimal plan with the agents involved in the plan. Agents whose utility falls below a certain level due to the plans of other agents negotiate with the causal agent to adjust their plans. If, after repeated negotiations, all agents have a certain level of utility, the plan is executed, and the simulation progresses for one period with each agent's decisions reflected in the material flow. By repeating the above, it is possible to effectively combine ISSCM with MAS.

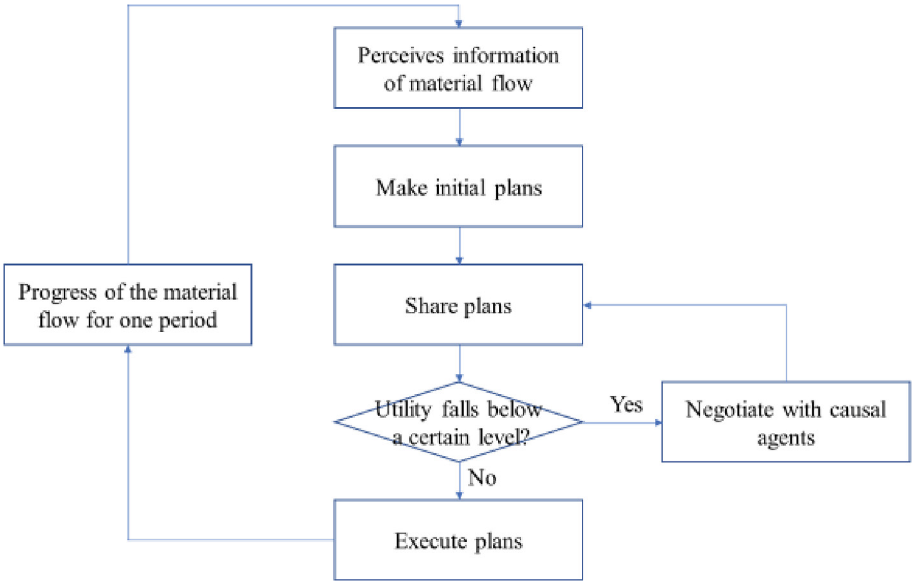

Fig. 3. Decision-making flow of each agent

4 Conclusion

This paper introduces the research concept of ISSCM using a multi-agent system. To implement SSC in the future, it is essential to operate multiple SSCM plans through an integrated approach, rather than independently. For each plan to operate efficiently, it is necessary to reduce the conflicts that occur among them. Therefore, this research concept aims to operate multiple SSCM plans simultaneously using LPP-based negotiation between agents. Through this research, we believe that we can support the social implementation of SSC by real decision makers by showing an example of execution of multiple plans for multiple tasks, while all agents maintain a certain level of utility.

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