ONE APPROACH TO SUPPLY CHAIN OPTIMIZATION FOR DECISION MAKING

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Abstract

This paper presented a study of evolutionary programming for the optimization of a supply chain network management. Decision making in distribution management and logistics is often based on collective behavior modeling of multi-agent systems. The supply chain was modeled as agent-based system for optimization of costs related to stocking, manufacturing, transportation and shortage. This is dynamic task, especially in a supply chain network that is becoming increasingly demanding, with customers expecting their products to be delivered as quickly as possible and according to their exact specifications. The main goal of this paper is to describe some views of multi-agent systems behavior modeling. The key technologies, which are based on the paradigm usually called *Collective Intelligence* of agent swarm, in which the system properties emerge from local interactions between elementary actions of single agents.

Keywords: multi-agent systems. Ccollective behavior. Multi-objective optimization.

1. Background

Information technology solutions such as decision support systems based on simulation and optimization systems are indicated as the way to directly support decision making on Supply Chain Management. Group control of reconfigurable agent networks is fundamentally a difficult problem, which can be based on use of principles of evolutionary programming in a monitoring and collective control within a studied area. Supply chain management can include factors relating to inventory, materials and production planning too in its concept. Logistics management is a part of the supply chain management that plans and implements the flow and storage of goods, services in order to meet the demands of the consumers. Supply chain network management takes care of the design, planning, execution, control, and monitoring of supply chain activities with the sole objective of creating net value and leveraging worldwide logistics. On the other hand logistics can be simply defined as the management of the flow of goods and the services between the point of origin and the point of consumption in order to meet the requirements of customers [1].

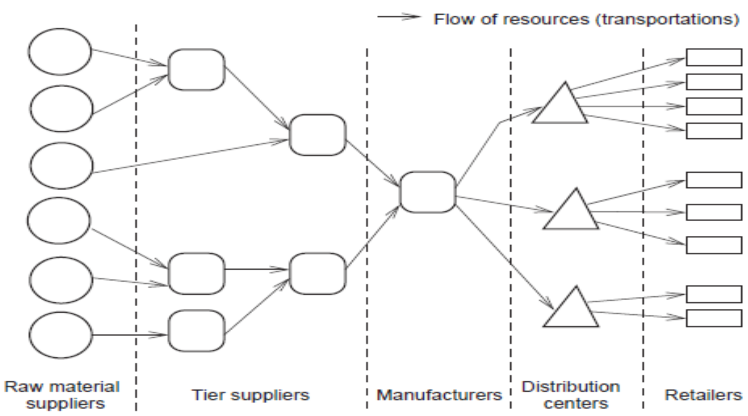

Fig.1

Generally in logistics we have to deal with distributed systems. To support the demanding management task the multi-agent approach offers promising perspectives. The theory of distribution management, based on a multi-agent concept, can be applied for the planning and control of distributed systems in which a larger number of actors (individuals) and agents (software objects) have to take decisions. System control as we have in mind for logistics systems embedded in a dynamic supply chain network is a management task. Our envisaged application field is logistics. We define logistics as the control of material, capital and information flow within an enterprise in view directed towards their global goals. As to their formal structure logistics systems have a lot of similarities. The purpose of the system is well defined, the goals are specified on a strategic and operational level. As to material, information and capital flow within the system their routing has to follow given directives. The logistics system is embedded in a dynamic supply chain network, where a permanent interaction between the logistics system and the supply chain network takes place.

We are interested only in agent-based management system as decision support tool, where agents in this tool propose solutions to well-defined decisions or take even decisions autonomously as far as decision competence is delegated to agents. The link of the management system with its logistics system to control can be realized in two ways, either to a representation in a simulation model or directly to the real world system.

2. Related Work

In this section we discuss collective agents, where researcher have attempted to think up ways to let agents cooperate with each other. A very concrete physical application area of collective intelligence is *collective agents*. We look at three different (partially overlapping) areas of interest within collective agents: *swarm agents* that takes the concept of swarming as its inspiration, *evolutionary agents* that takes evolution as the mechanism for adaptability in agents, and *behavior-based agents* where agents are programmed on the behavioral level.

Unfortunately unique approach to a problem of collective agents behavior modeling is not yet formed because of applied diversity. Provisionally, a swarm system can be defined as a collection of autonomous agents interacting with one another directly and locally, or indirectly (via changes in the supply chain network), and which collectively solve some distributed problem.

One distinguish two types of multi-agents controls: swarm and collective. Swarm control strategy, based on a Leader-Followers structure, assumes, that the members of group are not related one to others informational, whereas collective control means, that objects of group have the possibility of information exchange between them. Conditionally difference by completeness of information (few or much) between swarm and collective can be represented as (Figure 2):

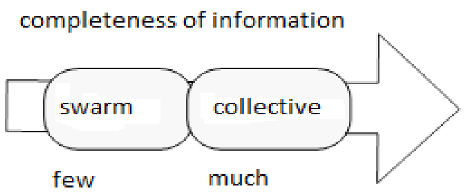

Figure 2

3. Problem formulation

In this section we give a brief description of the two supply chain decisions strategies (a centralized one and a decentralized one) dedicated for two different types of the behavior. In centralized strategies, there exists a single agent that manages the agents. As regarding decentralized strategies, management responsibilities are divided among the agents. As advantage of centralized group management strategy we can consider the simplicity of organization and algorithmization. However, this type of management is more applicable in cases of stationary structured supply chain network. Further, casual death of dispatching will become the cause of entire systems failure.

This section presents a formalization of the supply chain network agents collective decision making problems complexity estimation. The current state of integrated system “Agent group - Supply chain network” is a tuple [2]:

$$S(t) \in \langle A(t), B(t), T(t), D(t) \rangle \tag{1}$$

where there is a group *A* of *N* agents $A_i \ (i = 1, N)$ functioned in supply chain network *B*.

We can define the complete group of agents *A* under study as the vector-function:

$$A(t) = f_a(A_1(t), A_2(t), ..., A_N(t)). \tag{2}$$

where *N* is the number of agents.

The condition of supply chain network around the agent $A_i \in A$ at time *t*, generated by the stochastic demands (orders), can be determined by the vector-function:

$$B(t) = f_E(B_1(t), B_2(t), ..., B_N(t)). \tag{3}$$

where the elements $B_i(t)$ are the values of parameters of supply chain network defined by agents.

The problem solution of tasks distribution between agents $A_i \in A$, $(i = \overline{1, N})$ is related to the information of targets as set of effectiveness estimation d_{il} to make decisions $D_i(t)$ by A_i agent. The total executing supply chain network management action as collective decision making processes for agent group will be

$$D(t) = \sum_{i=1}^{N} D_i(t), \tag{4}$$

The current state of supply chain network management on interval $[t_0, t_f]$ consists in determination of functional estimating the quality of group management

$$S(t) = \int_{t_0}^{t_f} F(t, A(t), B(t), D(t))dt, \tag{5}$$

with respect the conditions (that the states of supply chain network, supply chain network configuration and agent group management actions).

The main problem of supply chain network management consists in determination such set of management parameters $\{d_{il}\}$ for agents $A_i \in A$ on interval $[t_0, t_f]$ (where t_0 – initial point of time or before functioning of group *A* and t_f – final moment of functioning of group *A*), when the extremum of function (6), estimating the sum of weight coefficients or of effectiveness $\{d_{il}\}$ between every pair of subtask $T_l \ (l = \overline{1, M})$ and agent $A_i \in A \ (i = \overline{1, N})$ as quality of collective decision, will be realized

$$Q(t) = \sum_{l=1}^{M} d_{i,l} \rightarrow \text{maximum} \tag{6}$$

with the requirements that the demand at each customer has to be satisfied.

In conclusion we can add, that collective management is always decentralized.

4. Metrics of Agent Group Behavior

In this section, we propose a number of metrics to evaluate the quality of multi-agent system behavior from viewpoint of optimization. Hence, we define some number of metrics such as order and entropy, which will help us in evaluation of performance of the swarming behavior. Further, they will be utilized in comparing the performance of different behaviors achieved through setting agent parameters or sensing characteristics to different values than the default ones.

In general, order, entropy and average angular velocity metrics are defined to measure the alignment, positional order and energy consumption of the agent group, respectively. The average forward velocity metric is also utilized as a secondary measure of the energy consumption, and is more convenient to use in some cases. Order (coherence or synergy) measures the angular order of the agents. Entropy measures the positional disorder of the particle swarm. Entropy is used in a number of classical approaches to clustering, as a means to drive the clustering process. This metric is calculated by finding every possible cluster combination, finding Shannon's information entropy of these clusters and then sum them up. We consider as metrics the rate of certain contradiction or collision between the vectors of control actions [3]. Each agent $A_i(t)$ defines its own vector of control action, when the given extremum of functional will be realized. In the end of the section, from viewpoint of multi-objective or vector optimization , we can note, that this kind of problems can be resolved successfully using Artificial Intelligence techniques.

In the case of Artificial Neural Network method application, we are required to calculate the estimation of the weight coefficients of the neural synapses $w_i(t)$ each agent $A_i \in A$ as [4]:

$$w_i(t) = \frac{s_i(t)}{\sum_{i=1}^{N} s_i(t)} \tag{7}$$

A sigmoidal neuron computes an output value according to:

$$S(t) = \sum_{i=1}^{N} A_i(t) w_i(t) \geq S^{Opt} = \sum_{i=1}^{N} A^*{}_i(t) w_i(t) \tag{8}$$

And finally we introduce the formulation of entropy, an application of Shannon's information entropy metric to agent groups that provides a quantitative measure of agent group collective behavior [5].

$$H_m = -\sum_{i=1}^{N} P\left(\frac{S^{Opt}}{\sum_{i=1}^{N} s_i(t)}\right) \log_2\left(\frac{S^{Opt}}{\sum_{i=1}^{N} s_i(t)}\right) \tag{9}$$

5. Supply chain optimization technique

In this section, we propose Particle swarm optimization (PSO) as a new population based optimization technique, which can find very good solutions efficiently and effectively in a virtual search space. The original PSO algorithm is discovered through simplified social model simulation.

According to the literatures overview, it's easy to know that the canonical PSO model consists of a swarm of particles, which are initialized with a population of random candidate solutions. Each particle has a position represented by a position-vector x_i (*i* is the index of the particle), and a velocity represented by a velocity-vector v_i [6].

The swarm is defined as a set: $X = \{x_1, x_2, \cdots, x_N\}$, of *N* particles or individuals (candidate solutions), defined as:

$$x_i = (x_{i1}, x_{i2}, \cdots, x_{in})^T \in A, \quad i = 1,2,\cdots,N$$

where A is the searching space.

The particles are assumed to move within the search space, *A*, iteratively. This is possible by adjusting their *position* using a proper position shift, called *velocity*, and denoted as:

$$v_i = (v_{i1}, v_{i2}, \cdots, v_{in})^T, \quad i = 1,2,\cdots,N$$

Velocity is also adapted iteratively to render particles capable of potentially visiting any region of *A*. If t denotes the iteration counter, then the current position of the *i*-th particle and its velocity will be henceforth denoted as $x_i(t)$ and $v_i(t)$, respectively. Velocity is updated based on information obtained in previous steps of the algorithm.

This is implemented in terms of a memory, where each particle can store the *best position* it has ever visited during its search. For this purpose, besides the swarm, *X*, which contains the current positions of the particles, PSO maintains also a *memory* set:

$$P = \{P_1, P_2, \cdots, P_N\}$$

which contains the best positions:

$$P_i = (P_{i1}, P_{i2}, \cdots, P_{in})^T \in A, \quad i = 1,2,\cdots,N$$

ever visited by each particle.

These dynamic parameters are defined as:

$$v_{ij}(t+1) = v_{ij}(t) + c_1 r_1 (P_{ij} - x_{ij}(t)) + c_2 r_2 (P_{gj} - x_{ij}(t)) \tag{10}$$

$$x_{ij}(t+1) = x_{ij}(t) + v_{ij}(t+1) \tag{11}$$

$$i = 1, 2, \cdots, N, \quad j = 1, 2, \cdots, n$$

where *t* stands for the iteration counter;

r_1 and r_2 are random variables uniformly distributed within [0,1];

c_1, c_2 are weighting factors, also called the *cognitive* and *social* parameter, respectively.

At each iteration, after the update and evaluation of particles, best positions are also updated. Thus, the new best position of x_i at iteration *t*+1 is defined as follows:

$$P_i(t+1) = \begin{cases} x_i(t+1), & if \quad f(x_i(t+1)) \le f(P_i(t)), \\ P_i(t), & otherwise \end{cases} \tag{12}$$

Based on the PSO paradigm, dynamic behavior of multi-agent system, cooperatively managing a supply chain network, each particle can apperceive the “Agent group - Supply chain network” state and make some decisions to modify its behavior intelligently. Each of particles represents a potential solution (or decision of multi-target distribution) to an optimization problem. The goal of algorithm is to converge to the global (over the search space) or local (into the particular cluster) optimum of a target function.

The presented approach is a distributed algorithm that partitions the supply chain network into a set of locally clusters. This is achieved by deriving a set of weight coefficient or estimation of effectiveness d_{il} between every pair of subtask T_l $(l = \overline{1,M})$ and agent $A_i \in A$, $(i = \overline{1,N})$ within the locality of each subset for selecting the best node of its neighborhood to become its leader. We envisage every the values of decision or management $D_i(t)$ as the “velocity” of each particle in given iteration. Moreover, the each pace is varied inversely of particular velocity.

6. Conclusion

This work is motivated by the idea that supply chain network management and logistics, should be realized by the distributed multi-agent systems. Relevance of problems is particularly pointed by the supply chain network dynamism of the shape of fitness function landscape, which consists of a number of peaks of changing with and height and in stochastic processes.

We have discussed the behavioral modeling of multi-agent systems, especially the case of decentralized collective management strategy, when each agent defines its own vector of decisions singly with a glance of its own position, the state of supply chain network, and the control actions of others agents, that is agent group make decision cooperatively. Entropy based metric to agent groups behavior has discussed.

From viewpoint of multi-objective optimization in multi-agent systems, it was noted, that this kind of problems can be resolved successfully using PSO techniques, including Artificial Neural Network method.

7. References

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გადაწყვეტილების მიღებისათვის მიწოდების ჯაჭვის ოპტიმიზაციის ერთი მეთოდის შესახებ

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რეზიუმე

განიხილება ევოლუციური დაპროგრამების საკითხი მიწოდების ჯაჭვის ქსელის მენეჯმენტის ოპტიმიზაციისთვის. გადაწყვეტილების მიღება ლოგისტიკასა და მართვაში განაწილებით ხშირად ემყარება მულტი-აგენტური სისტემების კოლექტიური ქცევის მოდელირებას. მიწოდების ჯაჭვი მოდელირებული იქნა, როგორც აგენტზე ორიენტირებული სისტემა იმ ხარჯების ოპტიმიზაციის-თვის, რომელიც უკავშირდება მომარაგებას, წარმოებას, ტრანსპორტირებას და დეფიციტს. ეს დინამიკური ამოცანაა, განსაკუთრებით მიწოდების ჯაჭვის ქსელში, რომელზეც სულ უფრო მეტად იზრდება მოთხოვნა მომხმარებლების მხრიდან. მათ სურთ მიიღონ პროდუქცია შეძლებისდაგვარად სწრაფად და სათანადო ტექნიკური პირობების შესაბამისად. სტატიაში აღწერილია გარკვეული მიდგომები მულტი-აგენტური სისტემების ქცევის მოდელირებასთან დაკავშირებით. ძირითადი ტექნოლოგიები, რომლებიც ემყარება პარადიგმას, ეგრეთ წოდებულ აგენტთა გუნდის კოლექტიურ ინტელექტს, რომელშიც სისტემური თვისებები გამოვლინდება ლოკალურ ურთიერთობებში ცალკეული აგენტების ელემენტარულ ქმედებებს შორის.

ПОДХОД К ОПТИМИЗАЦИИ ЦЕПЕЙ ПОСТАВОК ДЛЯ ПРИНЯТИЯ РЕШЕНИЯ

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Резюме

Представлено исследование эволюционного программирования для оптимизации управления сетью цепей поставок. Принятие решения в управлении распределением и логистике часто основано на моделирование коллективного поведения систем мультиагента. Цепь поставок была смоделирована как агентно-ориентированная система для оптимизации затрат, связанных со снабжением, производством, транспортировкой и дефицитом. Это - динамическая задача, особенно в цепи системы поставок, к которой все более и более увеличиваются требования клиентов, ожидающих, что их продукты будут поставлены в срок по мере возможности. Главная задача описать некоторые представления о моделировании поведения систем мультиагента. Ключевые технологии, которые обычно основаны на парадигме под названием Коллективный разум роя агентов, в котором системные свойства появляются из местных взаимодействий между элементарными действиями единичных агентов.