A New PSO Scheduling Simulation Algorithm Based on An Intelligent Compensation Particle Position Rounding off

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Abstract

The PSO algorithm belongs to the consecutive space optimizing family, whereas, a scheduling problem is a typical discrete space, non-numeral optimizing problem. What kind of particle representing method should be used to map the solution of a scheduling problem; how to map between consecutive space where the PSO falls and discrete space where the solution of a scheduling problem falls; how to design and improve the PSO algorithm; how to adjust the PSO algorithm's parameters to make it work for a scheduling problem; how on earth the PSO algorithm will behave on the scheduling problems, still need to be investigated. Therefore in this paper, in accordance with the characteristics of the scheduling problems, we put forward an appropriate scheme to generate the schedule sequence indirectly by decoding the particles, and we also proposed a new particle representing method called Intelligent Compensation Particle Position Rounding off (ICPPR). Each particle corresponds to an Agent, and the population of particles forms a particle coalition, so a multi-agent coalition forms meanwhile. Therefore, the intelligent compensation rounding-off operations for each particle in the coalition is actually a negotiation between multi-agent coalitions. Finally, the PSO algorithm based on the ICPPR particle representing method had been used for a river scheduling problem, the calculation results showed that Multi-Agent particle swarm algorithm based on the ICPPR has the obvious advantages in the algorithm calculation cost and stability.

1. Introduction

The Particle swarm optimization (PSO) algorithm was inspired by the coordinated search for food which lets a swarm of birds land at a certain place where food can be found. The PSO algorithm, whose mathematical model is presented in explicit formulation and can be conducted and operated easily, is a kind of evolution algorithm that based on the swarm intelligence. After analyzing the current studies of the PSO algorithm, we have found that following problem exists. The PSO algorithm belongs to the consecutive space optimizing family, thus, how to apply the PSO algorithm to the discrete space optimization remains a key area of researching. Whereas, a scheduling problem is a typical discrete space, non-numeral optimizing problem, for which the PSO research achievements are still scarce [1][2]. Moreover, the main part of solving a scheduling problem is deciding the scheduling algorithm, which makes the research on PSO algorithm for the scheduling problem meaningful and helpful.

It seems, after analyzing the interrelated documents on the PSO algorithm, that there're no systematic researches on classical scheduling problems, such as Flow Shop, Job Shop or Parallel Machine Scheduling, which lay the foundation for many other theories and the practical scheduling problems [3][4]. As for the PSO algorithm, the particle position parameters fall into the real number field, so it's impossible to use the a particle to represent a schedule sequence directly, whose value falls into the field of integer. For different scheduling problems, such as Job Shop, Flow Shop and Parallel Machine Scheduling, questions like what kind of particle representing method should be used to map the solution of a scheduling problem; how to map between consecutive space where the PSO falls and discrete space where the solution of a scheduling problem falls; how to design and improve the PSO algorithm; how to adjust the PSO algorithm's parameters to make it work for a scheduling problem; how on earth the PSO algorithm will behave on the scheduling problems, still need to be investigated. The parameters of any optimizing algorithm play a very important role in the behavior of that algorithm. But current researches on the PSO algorithm focused mainly on its behavior in the consecutive space and there're no such documents concerning its behavior in the discrete space.

Therefore in this paper, in accordance with the characteristics of the scheduling problems, we put forward an appropriate scheme to generate the schedule

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sequence indirectly by decoding the particles, and we also proposed a new particle representing method called Intelligent Compensation Particle Position Rounding－off (ICPPR).

2. The Particle Representing Method

The particle representing method based on a particle position rounding-off strategy can be applied whenever the target solution is a better allocation of the multiple resources. As for the Multi-Resource Scheduling problems, suppose the total amount of the tasks to be scheduled is denoted by N; the total number of the resources is a positive integer m, and we use different natural numbers from 1 to m to denote different resources, thus, we can build an two-dimensional particle with the length N, whose first dimension represents the tasks to be scheduled (denoted by different natural numbers 1, 2, 3, ..., N), and the second dimension represents the position of this particle. This two-dimensional particle can be illustrated as following:

Tasks to be scheduled	1	2	…	j	…	N
Particle position（x_i）	x_{i1}	x_{i2}	…	x_{ij}	…	x_{iN}

To consider the above-mentioned two-dimensional particle, the particle position vector components xij are restrained in the natural number range [1, m+1], so for each to-be-scheduled task j, we should make an intelligent compensation rounding-off to ensure that [5]. And this kind of rounding-off must make sure that each particle can get a satisfying position, as to the PSO algorithms based on the Multi-Agent, this kind of intelligent compensation rounding-off is a consultation process carried out by multiple agent systems, so in this paper, we'll propose a consultation model based on the game theory to implement the intelligent compensation rounding-off for each particle position vector. This process is denoted by NEG (x_{ij}) (NEG (x_{ij})∈[1, m]) in this paper, thus, for any to-be-scheduled task j, it will be assigned to the resource denoted by NEG (x_{ij}). Hence, we can get a resource allocation plan Si for all the N tasks to be scheduled, that is, a solution to the scheduling problem or a schedule program. It's obvious now that we can create a mapping function between the solution of a scheduling problem and the position of a particle by implementing the intelligent compensation rounding-off, as showed in figure1. We'll abbreviate this method to ICPPR in this paper.

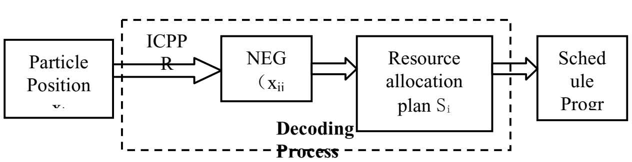

Figure1. Mapping from Particle Positions to a Schedule Program

2.1 Decoding Process

The decoding process for the particle representing method based on ICPPR is relatively simple from the perspective of its mapping relationship between the particle position vector and the solution space of a scheduling problem. A schedule program can be obtained just by applying the intelligent compensation rounding-off operation to a particle's position vector components.

2.2 Velocity-Position Model

In the particle representing method based on ICPPR, the updating process of a particle's position vector is shown in Figure2. After being updated by this Velocity-Position model, each particle's position vector represents a new schedule program. During the updating process, special attention should be paid to make sure that xij is restricted in the range of [1, m+1] so that NEG（x_{ij}）∈[1,m].

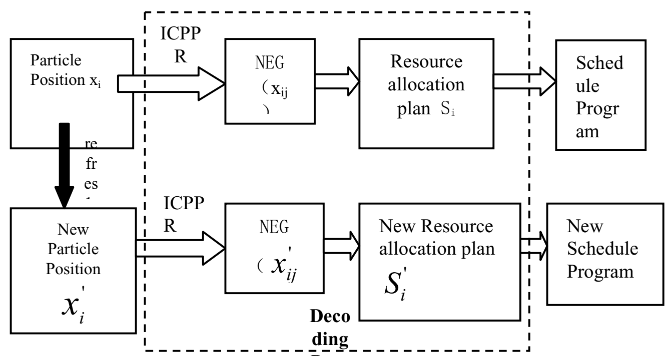

Figure 2. Particle Position Round off Operation Steps

3. A Particle Position Vector Rounding-off Algorithm Based on An Intelligent Compensation

3.1 Formation of Particle Coalition

In the PSO algorithm based on the Multi-Agent discussed in this paper, each particle corresponds to an Agent, and the population of particles forms a particle coalition, so a multi-agent coalition forms meanwhile. Therefore, the intelligent compensation rounding-off operations for each particle in the coalition is actually a negotiation between multi-agent coalitions [7]. This kind of multi-agent negotiation can be formulation described as:

Let T be a schedule task, and $A = (a_1, a_2, \Lambda\ \Lambda\ , a_n\}$ be a set composed by n Agents (particles). Suppose the consumption time (execution time) for Agenti to schedule T is denoted by ci (ci >0), and the return (of benefits and services) is denoted by ri (ri >0), hence we can get a consumption vector $C=\{c_1,c_2,\Lambda\Lambda,c_n\}$, and a return vector $R=\{r_1,r_2,\Lambda\Lambda,r_n\}$. The return vector (a return vector here can be comprehended as the utility vector of an Agent under certain countermeasure) is defined as:

$$P=R-C=\{r_1-c_1,r_2-c_2,\Lambda\Lambda,r_n-c_n\}=\{p_1,p_2,\Lambda\Lambda,p_n\}$$

For some schedule task T, where the Agent arrange-alliance Am participants, Am is a subset of set A (Agent Set), namely Am∈A, hence, Am could be extended to A, with its corresponding return vector becomes: $P_m=\{p_{1m},p_{2m},\Lambda\Lambda,p_{nm}\}$,

in which, $p_i>0\ \ (a_i\in A_m)$

$p_i=0\ \ (a_i\in A,\ \exists a_i\notin A_m)$.

$\forall a_i\in A$, the expected arrange-alliance Ak should satisfy:

$$p_{ik}=\max_m p_{im} \tag{1}$$

, which means that ai expects more benefits in the arrange-alliance it participants. Therefore, when the Agents in set A combine into arrange-alliance, their target functions usually can not be satisfied simultaneously, that is, competition exists among them. Hence, the problem we faced when we apply a rounding-off operation to a particle's position vector during a Multi-Resource schedule can be abstracted into: how to form a arrange-alliance among each Agents under this competitive circumstances.

Meanwhile, the Agent members that may form an arrange-alliance cannot be foresaw because of the dynamic characteristic of the set A. The dynamic characteristic of Multi-Agent system, which means the appearance and withdrawal of any Agent in some arrange-alliance is uncertain, makes it impossible to determine the members of set A beforehand during the process of forming the arranger-alliances.

Moreover, the autonomy of an Agent makes it possible to decide whether to and how to select a schedule task on the basis of both global superiority and itself condition. To simplify the issue, we assume the composition of an arrange-alliance satisfies the additivity, namely:

$$v(A_1)+v(A_2)\le v(A_1\cup A_2),(A_1\cap A_2=\phi) \tag{2}$$

, in which, $v(A_1)$ denotes the benefits A1 can get after it have executed task T.

Formula (2) shows that the arrange-alliances formed among the Agents can create more profit than the summation of the profit created by the individuals in the alliance, thus, more profit for the individuals, averagely.

The assumption that the composition of an arrange-alliance satisfies the additivity has its practical significance. Every Agent in this alliance can coordinate with each other because of the form of the arrange-alliance. From another point of view, the worst case in the arrange-alliance is that each Agent works as individual as if they've never formed an alliance, that is, the return of the arrange-alliance is no less than that of before the formation of the alliance. In brief, the additivity makes the Agents hope to form an alliance more than before, thus, making all the alliances executing different tasks form a larger arrange-alliance regardless of the correlations among these tasks [6].

The negotiation process is shown as Figure3:

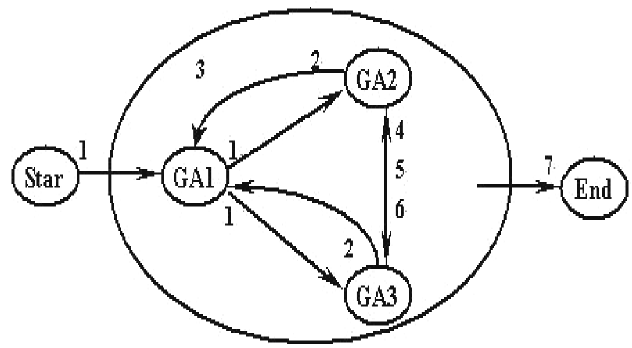

Figure3. NMBGT Negotiation Process

sequence numbers 1-7 indicate the negotiation steps:

(1) certain Agent raise a claim for the rounding-off operation to its particle space position vector, and broadcast this information to all the Agents in the system;

(2) Agents that are participating in this schedule task or competing for this resource give out their expecting utility value and their willingness to join this negotiation theme;

(3) All the agents that are willing to join this negotiation form an arrange-alliance A, and all the Agent's initial expecting utility values are obtained simultaneously, and all the Agent's minimum utility values are given out before intercomparison;

(4) Agents participating in this negotiation exchange their initial utility values and obtain the real-time utility functions;

(5) All the Agents in the arrange-alliance give out corresponding countermeasures on this negotiation theme;

(6) All the Agents in this arrange-alliance negotiate and bargain on the countermeasures given out by themselves until a uniform countermeasure reached;

(7) Agents in this arrange-alliance won't compromise to each other, and then this alliance gets dissolved.

3.2 The multi-Agent consultative mechanism of taking entire operation to the particle alliance position

The particle position in each renewable process, obtains superior or the most superior space position, but these positions are continual, it can not be directly mapped the resource scheduling and allocation plan, so need to take the entire operation to the solutions, Logistics institute's Liu Dr. Zhixiong in Wuhan University of Technology proposed that one kind of algorithm which takes the entire operation directly, the algorithm is taking the nearest whole number operation to the space position directly, which is mapped to resource scheduling and allocation plan, this method is simple and easy to operate, but this operation can not directly and effectively respond to the wishes (benefits) of particle itself, because it is not a simple linear relationship between the benefits that the particle obtained and the space position, therefore this whole operation exists a big error. In the algorithm research, we find that wishes (benefits) of the interaction between the particles in the obtained programme are interrelated, the most superior and the superior plan is that the all of particle in the particle alliance can get the largest aspirations as far as possible. This expression of the will is very similar to the traditional response of the N-person cooperative game, therefore in this article, thus in this paper after a particle Union, in the process of updating the particle's position in the alliance, carries on the multi-Agent consultation in the particle alliance, particles through consultations obtain the mapping from the spatial position to the resource scheduling and allocation plan, which best meets the wish's expression of the particle itself after taking the entire.

In the traditional agent consultative mechanism which use game theory, generally uses two-person zero-sum game and the multi-objective synthesis judgment method. In the multi-agent consultative constitution under this topic research, taking into account the particle Agent participants in the consultations, that is a process what seeks the goal in itself for optimal. But because of the limitation of benefits, the consultative process is the process of competing between each Agent. This process is similar to the N-person cooperative game problems in the theory of games. It is not zero-sum, but a mutual consultation, win-win process. Based on the above design idea, in this paper, on the basis of countermeasures the definition of the Multi-Agent System consultation mechanism NMBGT (Negotiation Mechanism Based on Game Theory) is given. A consultative process of NMBGT can be considered as an Agent initiated by the Agent with one or more of the space in a collection of threads consultations Agent. The consultation mechanism NMBGT can be defined as an Eight tuples:

$$\{GA, OptA, CA, TA, OA, AA, Time, Thread, \Pr otocol\}$$

. GA: Participation consultation process Agent set (particle population).

$OptA$: Goal community in the consultative Agent set in each Agent respective consultation problems. Because NMBGT is on the scheduling problem of the multi-resources, each Agent belongs in research goal community.

CA: Type of Consults in the Agent set in each Agent respective consultative question. As the case in OptA, the issues researched in NMBGT, each Agent belong to the types of issues faced by the division, each one has its own mandate Agent, it is an important attribute in their participation in the Multi-Agent consultations.

TA: The set of several consultative themes about the Consultations problems.

OA: The set of consultations themes is the public knowledge in the participants in the consultations between Agents.

AA: The set of utility values in Agent consultations.

$Time$: The Agent system clock that Agents participate in and indicated by the natural order of number.

$Thread$: Consultative thread.

$\Pr otocol$: Consultative protocol based on Game Theory.

For an Agent of a system, an invitation is given based on the particles space position on the entire operation form, and then the corresponding messages is sent individually in the form of broadcast in the GA. For the Agent which participates in the scheduling tasks and competing in the resources also participating in the consultative themes, a alliance A is formed, in which each - Agent indicates its expected utility value of the theme of the consultations in the process of consultation itself (that is, the desired position of the particle itself). In accordance with their expectations and consultation, the utility values can be given, after mutual discussion and compromise, each gets a final recognition of the effective value or failure as the end of the consultation process.

4 Algorithm experiment

In this paper, in comparison with reference [7], where we use a kind of the particle swarm optimization algorithm based on the nearest whole number rounding－off, and another PSO based on intelligent compensation particle position rounding－off to computing, set two algorithms for the total number of iterations 1000, and end the iteration when the optimum value is less than 0.001.

The comparative analysis of the stability of the two algorithms is shown as Figure 4.

Figures 4 and 5 is the map of using the general rounding－off and the intelligent compensation particle position rounding－off to solve the full and empty rate situations of the Shanghai inland waterway Ship Navigation Channel, what can be seen from Fig, the all rivers' full and empty rate situations reduce significantly when using he PSO algorithm based on ICPPR to schedule, thus can be able to more fully guarantee the effective use of every river, and guaranteeing that the inland waterway ships navigate smoothly.

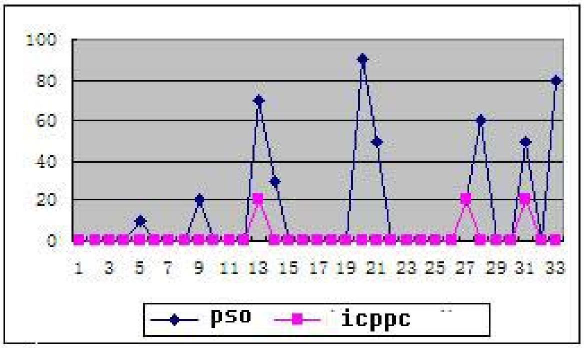

Figure4. Distribution Map of the full rate situation of the channel that is asked and solved by this two kinds of algorithms

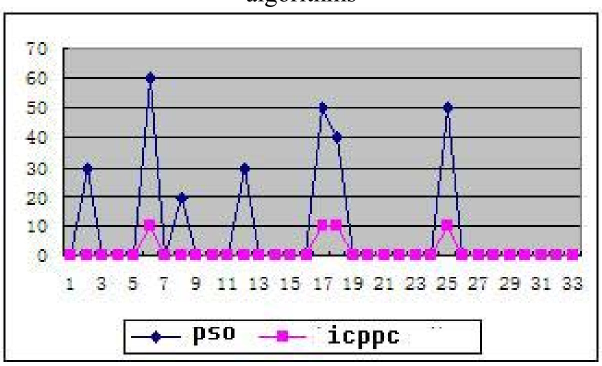

Figure5. Distribution Map of the empty rate situation of the channel that is asked and solved by this two kinds of algorithms

5 Conclusions

This paper analyzes the existing problems when using particle swarm algorithm to deal with the scheduling problem, and explicitly indicating that using the appropriate kind of particle representing method to map the solution of a scheduling problem is the key to solving the problem, and pointing out the key issues that need to be resolved when designing particle representing method.

Against the features of multiple resources for dynamic scheduling and configuration problems, we proposed a particle representing method called Intelligent Compensation Particle Position Rounding－off(ICPPR), and gives Multi-Agent particle swarm algorithm's solving steps to solve the problem of more resources dynamic scheduling.

Finally, the PSO algorithm based on the ICPPR particle representing method had been used for a river scheduling problem, the calculation results showed that Multi-Agent particle swarm algorithm based on the ICPPR has the obvious advantages in the algorithm calculation cost and stability.

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