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Particle Dynamics Approach to Multi-Agent Systems

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Abstract— **The resources allocation and task assignment in complex distributed network environment is a typical problem of multi-agent systems (MAS). Even without taking into account interactions, coordinations, and a variety of random phenomena in networks, the bandwidth allocation problem in ATM networks is also NP-complete. This paper presents a particle dynamics approach (GPDA) that transforms the MAS problem-solving into the kinematics and dynamics of particles in a force-field. As an important application for problem-solving in MAS, this paper uses GPDA to optimize the bandwidth allocation and $Q \circ S$ in ATM networks. The GPA has features in terms of the high-degree parallelism, multi-objective optimization, multi-type coordination, multi-granularity coalition, and easier hardware implementation. Simulations and comparisons show the effectiveness and suitability of GPDA.**

I. INTRODUCTION

Since the ATM network is to support multiple classes of traffic (e.g. video, audio, and data) with widely different characteristics and Quality of Service (QoS) requirements, one of the major challenges is to guarantee the promised QoS for all the admitted users, while maximizing the resource utilization through dynamically allocating appropriate resources (e.g. bandwidth, buffers). The bandwidth allocation problem in ATM networks is NP-complete [1]. There are a lot of algorithms and strategies for the bandwidth allocation, such as maximizing an aggregate users' utility function, an average priority or average reliability of traffics; minimizing the overhead of data transmission or the highest call blocking probability of all source-destination pairs. Duality models in [2]-[8] use a primal parallel algorithm for allotted rates, and a dual parallel algorithm for shadow prices or congestion signals. However, most of the existing methods for networks optimization don't consider the complex factors in networks, such as various interactions, random failures, different autonomy and personality of network entities. In this sense, the resources allocation and task assignment in complex distributed network environment is a typical problem of multi-agent systems (MAS).

The distributed artificial intelligence has become one of the most interesting and challenging areas since the last decade. But most of approaches currently used to problem-solving in MAS have below limitations and disadvantages:

- Not consider the complex environment related to multi-type coordinate, multi-degree autonomy, multi-objective optimization and multi-granularity coalition.
- Not consider complex coordinations such as unilateral, unaware and unconscious coordinations, besides bilateral and conscious cooperation or competition.
- Only consider completely unselfish or completely selfish entity which tries to increase either the aggregate utility or personal utility.
- Need the global control, global information access and global objective, hence lead to series or small-scale parallel computation.
- Not consider stochastic, emergent and concurrent phenomena such as congestion, failure and priority change.

In order to overcome the above limitations, this paper proposes a novel generalized particle dynamics approach (GPDA) for problem-solving in MAS, and applies it to optimize the bandwidth allocation and $Q \circ S$ of ATM networks in complex environment. GPDA has features in terms of the high-scale parallelism, multi-objective optimization, multi-type coordination, multi-degree autonomy, multi-granularity coalition, and easier hardware implementation. GPDA can also deal with a variety of complex phenomena, including the random failure, emergent congestion, and dynamical priority. Simulations and comparisons show the effectiveness and suitability of GPDA.

II. GENERALIZED PARTICLE DYNAMICS

Without loss of generality, formalize the optimization of ATM networks as a problem-solving in MAS, where a link of networks is regarded as a resource agent, a virtual path connection (VPC) as a task agent, and a virtual channel connection (VCC) within a VPC as a subtask agent. Given a finite set $\mathcal{T}(\tau) = \{T_1, \cdots, T_m\}$ of m task agents and a finite set $\mathcal{A}(t) = \{A_1, \cdots, A_n\}$ of n resource agents in the time session τ, the resource agent A_i provides the task agent T_j with the bandwidth $a_{ij}(t)$ at time t, and meanwhile the task agent T_j offers the payment $p_{ij}(t)$ to resource agent A_i or obtains the hybrid $Q \circ S$ index $p_{ij}(t)$ from resource agent A_i. The resource agent A_i has the intention strength $\zeta_{ij}(t)$ for task agent T_j. For convenience, $a_{ij}(t)$, $p_{ij}(t)$ and $\zeta_{ij}(t)$ are normalized, such that $0 \leq a_{ij}(t) \leq 1$, $0 \leq p_{ij}(t) \leq 1$, and $-1 \leq \zeta_{ij} \leq +1$.

The conceptual diagram of a generalized particle dynamics approach (GPDA) to optimize the bandwidth allocation and $Q \circ S$ of ATM networks in complex environment is shown in Fig.1, where a particle corresponds to an agent, and

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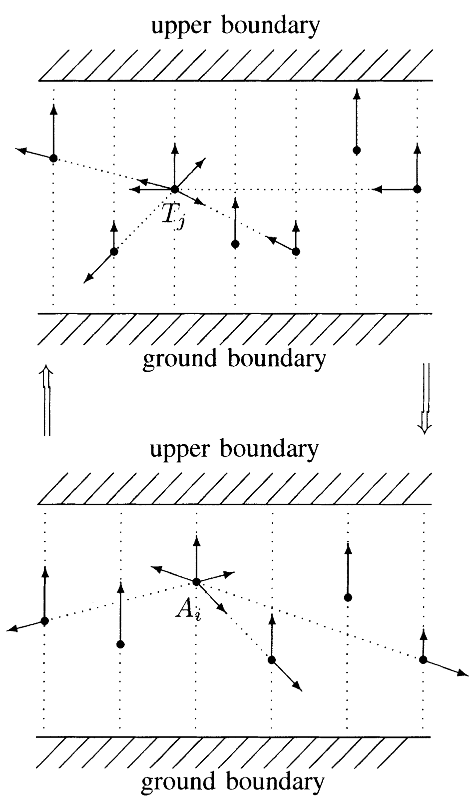
the resource force-field F_A and task force-field F_T form a duality model. A particle in a force-field may be driven by several kinds of forces. The gravitational force of a force-field tries to drive a particle to move towards boundaries of the force-field, which embodies the tendency to maximize the aggregate benefit. The pushing or pulling forces produced by other particles embody interactions among agents. The self-driving force on a particle represents the autonomy and personality of agent in MAS. Under the exertion of resultant force, every particle may move concurrently in a force-field. In this way, the GPDA transforms the problem-solving process in MAS into kinematics and dynamics of particles in the force-fields. When all the particles reach their equilibrium states, we then accordingly obtain the solution to the MAS optimization .

Task force-field F_T related to task agents



Resource force-field F_A related to resource agents

Fig. 1. The duality model of generalized particle dynamics approach (GPDA) to problem-solving in MAS, where the assignment policy of resource force-field F_A and the pricing policy of task force-field F_T influence each other.

Definition 1: The utility $U_{T_j}(t)$ and $U_{A_i}(t)$ of agent T_j and agent A_i, and the aggregate utilities $J_T(t)$ and $J_A(t)$ of force-fields F_T and F_A are defined respectively by

$$U_{T_j}(t) = \varsigma_1 \sum_{i=1}^{n} [1 - \exp[-x_{ij}(a_{ij}(t) - d_j)/p_{ij}(t)]] + \varsigma_2 [\sum_{i=1}^{n} x_{ij} p_{ij}(t) - q_j]; \quad (1)$$

$$U_{A_i}(t) = \varsigma_3 \sum_{j=1}^{m} \{1 - \exp[-x_{ij} p_{ij}(t)/|a_{ij}(t) - d_j|]\} + \varsigma_4 [r_i - \sum_{j=1}^{m} x_{ij} a_{ij}(t)]; \quad (2)$$

$$J_T(t) = \alpha_1 \sum_{j=1}^{m} U_{T_j}(t); \quad (3)$$

$$J_A(t) = \alpha_2 \sum_{i=1}^{n} U_{A_i}(t). \quad (4)$$

where $\varsigma_1, \varsigma_2, \varsigma_3, \alpha_1, \alpha_2$ are all positive constant; d_j and q_j are the desired bandwidth and the payment ability, respectively, of task agent T_j, and r_r is the maximal bandwidth of resource agent A_i. $x_{ij} = 1$ means that the j-th VPC passes the i-th link in networks.

Definition 2: The potential energy functions, $P_T(t)$ and $P_A(t)$, of the force-fields, F_T and F_A, respectively, are defined by

$$P_T(t) = \epsilon^2 \ln \sum_{j=1}^{m} \exp[-(U_{T_j}(t))^2/2\epsilon^2] - \epsilon^2 \ln m \quad (5)$$

$$P_A(t) = \epsilon^2 \ln \sum_{i=1}^{n} \exp[-(U_{A_i}(t))^2/2\epsilon^2] - \epsilon^2 \ln n \quad (6)$$

Where $0 < \epsilon < 1$.

Definition 3: The potential energy functions, $Q_T(t)$ and $Q_A(t)$, that are caused by the interactive forces among the particles respectively in F_T and F_A, are defined respectively by

$$Q_T(t) = \sum_{j,k} \int_0^{U_{T_j}(t)} \{[1 + \exp(-\zeta_{kj} x)]^{-1} - 0.5\} dx, \quad (7)$$

$$Q_A(t) = \sum_{i,k} \int_0^{U_{A_i}(t)} \{[1 + \exp(-\zeta_{ki} x)]^{-1} - 0.5\} dx, \quad (8)$$

where the coefficient $\zeta_{j\,k}$ represents the interaction strength of the agent T_k with respect to the agnent T_j. $\zeta_{i,k}$ is the interaction strength of the agent A_k with respect to the agent A_i. We have $\zeta_{jk} > 0$, $\zeta_{ik} > 0$ for competition; $\zeta_{jk} < 0$, $\zeta_{ik} < 0$ for cooperation; and $\zeta_{jk} = 0$, $\zeta_{ik} = 0$ for no interaction.

Definition 4: The hybrid energy function of the particles, A_i and T_j, at time t is defined by

$$\Gamma_{A_i}(t) = -\lambda_{A_i}^{(1)} U_{A_i}(t) - \lambda_{A_i}^{(2)} J_A(t) + \lambda_{A_i}^{(3)} P_A(t) + \lambda_{A_i}^{(4)} Q_A(t), \quad (9)$$

$$\Gamma_{T_j}(t) = -\lambda_{T_j}^{(1)} U_{T_j}(t) - \lambda_{T_j}^{(2)} J_T(t) + \lambda_{T_j}^{(3)} P_T(t) + \lambda_{T_j}^{(4)} Q_T(t), \quad (10)$$

where $0 < \lambda_{A_i}^{(1)}, \lambda_{A_i}^{(2)}, \lambda_{A_i}^{(3)}, \lambda_{A_i}^{(4)}, \lambda_{T_j}^{(1)}, \lambda_{T_j}^{(2)}, \lambda_{T_j}^{(3)}, \lambda_{T_j}^{(4)} \le 1$.

Definition 5: Let the coordinate origin be located at the central line between the upper and bottom boundaries of force-field, and $C_{T_j}(t)$ be the vertical coordinate of particle T_j at time t, $C_{A_i}(t)$ be the vertical coordinate of particle A_i at time t. The particle dynamic equation for particle T_j and A_i are defined respectively by

$$\begin{cases} dC_{T_j}(t)/dt = \Psi_{T_j}^{(1)}(t) + \Phi_{T_j}^{(2)}(t) & (11) \\ \Psi_{T_j}^{(1)}(t) = -C_{T_j}(t) + \gamma_1 V_{T_j}(t) & (11a) \\ \Phi_{T_j}^{(2)}(t) = -w_{T_j} U_{T_j}(t) & (11b) \end{cases}$$

$$\begin{cases} dC_{A_i}(t)/dt = \Phi_{A_i}^{(1)}(t) + \Phi_{A_i}^{(2)}(t) & (12) \\ \Phi_{A_i}^{(1)}(t) = -C_{A_i}(t) + \gamma_2 V_{A_i}(t) & (12a) \\ \Phi_{A_i}^{(2)}(t) = -w_{A_i} U_{A_i}(t) & (12b) \end{cases}$$

where $\gamma_1, \gamma_2 > 1$, and

$$V_{T_j}(t) = \begin{cases} 0 & \text{if } C_{T_j}(t) < 0 \\ c_k^{(j)}(t) & \text{if } 0 \le C_{T_j}(t) \le 1 \\ 1 & \text{if } C_{T_j}(t) > 1, \end{cases} \quad (13)$$

$$V_{A_i}(t)=\begin{cases}0 & \text{if } C_{A_i}(t)<0\\ c_k^{(j)}(t) & \text{if } 0\leq C_{A_i}(t)\leq 1\\ 1 & \text{if } C_{A_i}(t)>1,\end{cases} \quad (14)$$

$$w_{T_j}=\exp[-(U_{T_j}(t))^2/2\epsilon^2]/\sum_{j=1}^{m}\exp[-(U_{T_j}(t))^2/2\epsilon^2],$$

$$w_i=\exp[-(U_{A_i}(t))^2/2\epsilon^2]/\sum_{i=1}^{m}\exp[-(U_{A_i}(t))^2/2\epsilon^2].$$

GPDA-Based Parallel Algorithm:

Costep 1.Initiate in parallel $a_{ij}(t_0)$, $p_{ij}(t_0)$, $\zeta_{ij}(t_0)$, $C_{A_i}(t_0)$ and $C_{T_j}(t_0)$ for $i\in\{1,\cdots,n\}, j\in\{1,\cdots,m\}$.

Costep 2. By the Eq.(1),(2), calculate in parallel the utility $U_{T_j}(t)$ and $U_{A_i}(t)$ of every particle T_j and A_i in force-fields at time t, respectively;

Costep 3. Calculate in parallel $C_{T_j}(t)$ by Eq.(11), and $C_{A_i}(t)$ by Eq.(12) of every particle.

Costep 4. If all particles reach their equilibrium states at time t, then finish with success; Otherwise, modify a_{ij} and p_{ij} by the following Eqs.(13), (14), respectively, then go to Costep 2.

$$dp_{ij}(t)/dt = \frac{\partial\Gamma_{T_j}(t)}{\partial p_{ij}(t)}-\lambda_{T_j}^{(5)}C_{T_j}(t) \quad (13)$$

$$da_{ij}(t)/dt = \frac{\partial\Gamma_{A_i}(t)}{\partial a_{ij}(t)}-\lambda_{A_i}^{(5)}C_{A_i}(t) \quad (14)$$

where $0<\lambda_{T_j}^{(5)},\lambda_{A_i}^{(5)}\leq 1$.

III. PROPERTIES OF GPDA

The properties of GPDA regarding the correctness, convergency and stability are summarized as follows, the detailed proof similar to [1] and omitted here.

Lemma 1: Eqs. (13), (14) enable the agnets, A_i and T_j, to increase the personal utility $U_{A_i}(t)$ and $U_{A_i}(t)$, in direct proportion to $(\lambda_{A_i}^{(1)}+\alpha_2\,\lambda_{A_i}^{(2)})$ and $(\lambda_{T_j}^{(1)}+\alpha_1\,\lambda_{T_j}^{(2)})$, respectively.

Lemma 2: Updating p_{ij} and a_{ij} by Eqs.(13), (14) gives rise to monotonic increase of the aggregate utility $J_T(t)$ and $J_A(t)$ of resource agents and task agents, respectively in direct proportion to $\alpha_1\lambda_{T_j}^{(2)}$ and $\alpha_2\lambda_{A_i}^{(2)}$.

Lemma 3: If ϵ is very small, then decreasing the potential energy $P_T(t)$ and $P_A(t)$ of Eq. (5), (6) amounts to increasing the minimal personal utility of task agents and the minimal personal utility of resource agents, respectively.

Lemma 4: Updating p_{ij} and a_{ij} by Eqs.(13), (14) gives rise to monotonic increase of the minimal personal utility of agents.

Lemma 5: Updating p_{ij} and a_{ij} by Eqs.(13), (14) gives rise to monotonic decrease of the potential energy $Q_T(t)$ and $Q_A(t)$, respectively in direct proportion to $\lambda_{T_j}^{(4)}$ and $\lambda_{A_i}^{(4)}$.

Theorem 1: Updating p_{ik} and a_{ik} by Eqs.(13), (14) gives rise to monotonic decreasing the hybrid energy function $\Gamma_{T_j}(t)$ and $\Gamma_{A_i}(t)$, where every agent may autonomously determine its optimization objective according to its own personality and intention.

Theorem 2: The GPDA algorithm can dynamically optimize in parallel the task allocation and resource allocation in MAS in the context of multi-type social coordination, multi-degree autonomy and multi-objective of individual agents.

Lemma 6: If $\gamma_1-1>-\Psi_{T_j}^{(2)}(t)>0$, $\frac{\partial\Psi_{T_j}^{(2)}(t)}{\partial C_{T_j}(t)}<1$ for $C_{T_j}(t)<0$ and $C_{T_j}(t)>1$; and $\frac{\partial\Psi_{T_j}^{(2)}(t)}{\partial C_{T_j}(t)}\geq 1-\gamma_1$ for $0<C_{T_j}(t)<1$ remain valid, then a stable equilibrium point of the particle T_j will be either $(C_{Tj}(t)<0, V_{T_j}(t)=0)$ or $(C_{T_j}(t)>1, V_{T_j}(t)=1)$. Similar conclusion is valid for the particle A_i.

Lemma 7: If $\gamma>1, -\Psi_{T_j}^{(2)}(t)<0$ and $\frac{\partial\Psi_{T_j}^{(2)}(t)}{\partial C_{T_j}(t)}<1$ for $C_{T_j}(t)>1$ remain valid, then a stable equilibrium point of the particle T_j will be $(C_{T_j}(t)>1,\ V_{T_j}(t)=1)$. Similar conclusion is valid for the particle A_i.

Lemma 8: If $\gamma_1>1, -\Psi_{T_j}^{(2)}(t)>\gamma_1-1$ and $\frac{\partial\Psi_{T_j}^{(2)}(t)}{\partial C_{T_j}(t)}<1$ for $C_{T_j}(t)<0$ remain valid, then a stable equilibrium point of the particle T_j will be $(C_{T_j}(t)<0,\ V_{T_j}(t)=0)$. Similar conclusion is valid for the particle A_i.

Lemma 9: If $\gamma_1>1$, $\frac{\partial\Psi_{T_j}^{(2)}(t)}{\partial C_{T_j}(t)}<1$ for $C_{T_j}(t)=1^{+0}$ and $\frac{\partial\Psi_{T_j}^{(2)}(t)}{\partial C_{ik}(t)}\geq 1-\gamma_1$ for $C_{T_j}(t)=1^{-0}$ remain valid, then the equilibrium point $(C_{T_j}(t)=1,\ V_{T_j}(t)=1)$ is saddle point. Moreover, if $\gamma_1>1$, $\frac{\partial\Psi_{T_j}^{(2)}(t)}{\partial C_{T_j}(t)}<1$ for $C_{T_j}(t)=1^{-0}$ and $\frac{\partial\Psi_{T_j}^{(2)}(t)}{\partial C_{T_j}(t)}\geq 1-\gamma_1$ for $C_{ik}(t)=1^{+0}$ remain valid, then the equilibrium point $(C_{T_j}(t)=0,\ V_{T_j}(t)=0)$ is saddle point. Similar conclusion is valid for the particle A_i.

Theorem 3: If $\gamma_1>1$ and $0\leq C_{T_j}(t_0)\leq 1$ remain valid, then the dynamical Eq. (11) has a stable equilibrium point iff $0<-\Psi_{T_j}^{(2)}(t)<\gamma-1$. Similar conclusion is valid for the particle A_i.

Theorem 4: If the condition of Theorem 3 remains valid, then GPDA can converge to a stable equilibrium state.

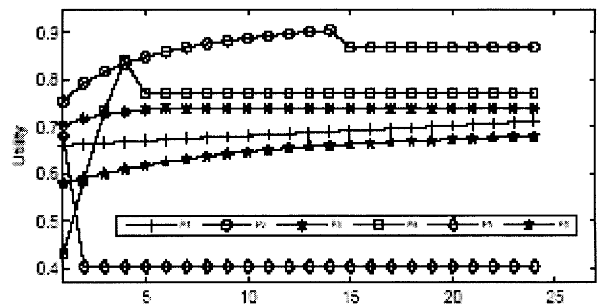


Fig. 2. The transients of individual utilities for six task particles in the force-field F_T during the execution of the GPDA algorithm, each task agent particle corresponding to a VPC in ATM networks. Simulation parameters are as follows: problem scale: 25 × 50, $\varsigma_1=\varsigma_2=\varsigma_3=\varsigma_4=0.5$, $\epsilon=0.2$, $\alpha_1=0.1$, $\alpha_2=0.5$, $\lambda_{T_j}^{(1)}=\lambda_{T_j}^{(2)}=\lambda_{T_j}^{(3)}=\lambda_{T_j}^{(4)}=\lambda_{T_j}^{(5)}=0.1$, $\lambda_{A_i}^{(1)}=0.2$, $\lambda_{A_i}^{(2)}=\lambda_{A_i}^{(3)}=0.9$, $\lambda_{A_i}^{(4)}=0.5$, $\lambda_{A_i}^{(5)}=0.1$, $\gamma_1=\gamma_2=1.1$.

• *Evolutionary process of utilities of agents:* The transients of personal utilities of several typical agents during executing the GPDA algorithm are shown in Fig.2 and Fig.3. The transients of aggregate utilities of all the resource agents and task agents during executing the GPDA algorithm are shown in Fig.4 and Fig.5, respectively. It can been seen that all particles evolve simultaneously to their stable equilibrium states.

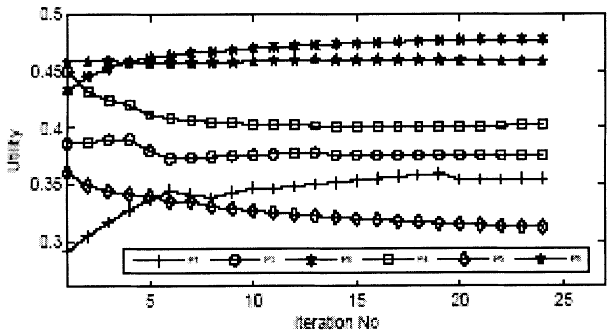


Fig. 3. The transient of individual utility for six resource particles in the force-field F_A during the execution of the GPDA algorithm, each resource particle corresponding to a link in ATM networks. Simulation parameters are the same as Fig.2.

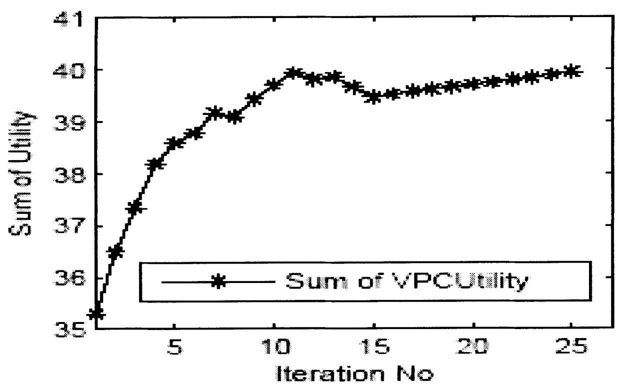


Fig. 4. The transient of aggregate utility of all the task particles in the force-field F_T during the execution of the GPDA algorithm, each task particle corresponding to a VPC in ATM networks. Simulation parameters are the same as Fig.2.

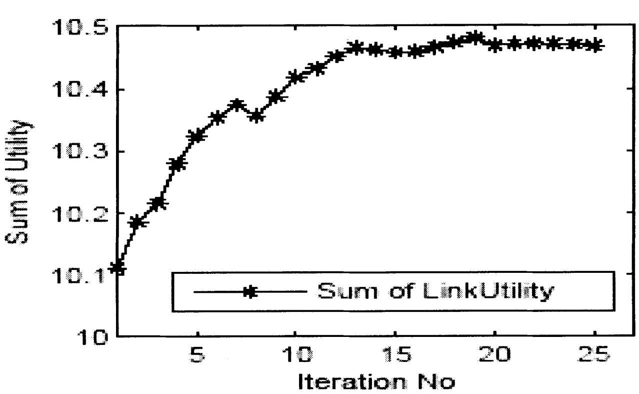
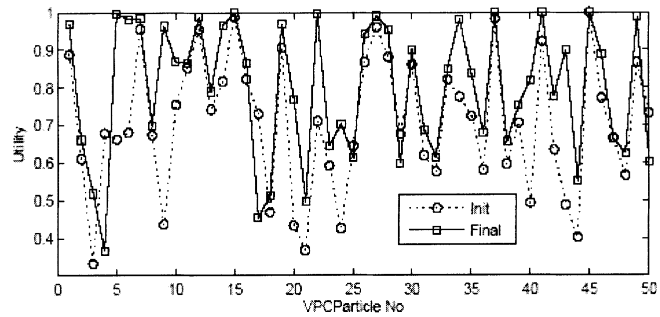


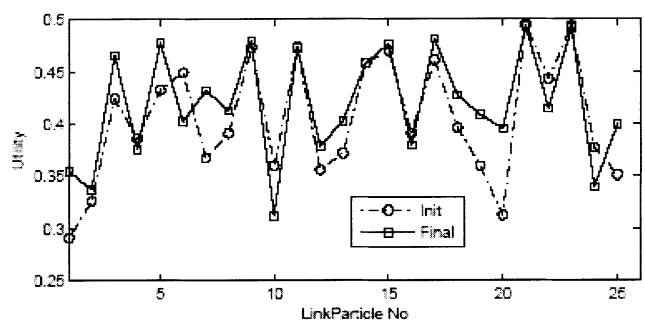
Fig. 5. The transient of aggregate utility of all the resource particles in the force-field F_A during the execution of the GPDA algorithm, each resource particle corresponding to a link in ATM networks. Simulation parameters are the same as Fig.2.

• *Evolutionary process of particle positions in force-fields:* The distributions of initial positions and final positions of task particles (i.e. VPC agents in ATM networks) in the force-field F_T and resource particles (i.e. link agents in ATM networks) in the force-field F_A during the execution of GPDA are shown in Fig.6(a) and Fig.6(b), respectively.

• *Evolutionary process of the bandwidths and the $Q \circ S$ indexes:* The transients of the allocated bandwidth and obtained $Q \circ S$ indexes of VPC agents in ATM networks during the execution of the GPDA algorithm are shown in Fig.7 and Fig.8, respectively.



(a). The transient of task agent particles in force-field F_T



(b). The transient of resource agent particles in force-field F_A

Fig. 6. The transient of particle positions in force-fields during the execution of the GPDA algorithm, each task agent particle corresponding to a VPC in ATM networks, and each resource agent particle corresponding to a link in ATM networks.

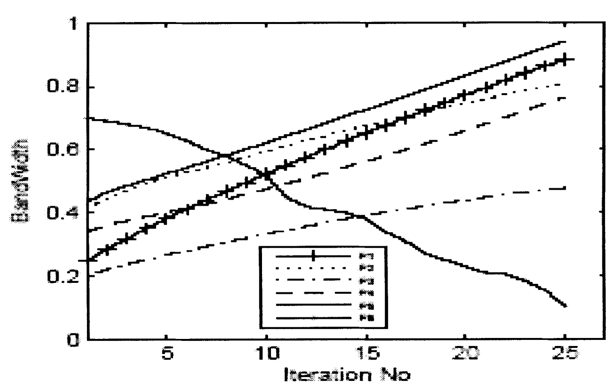


Fig. 7. The transients of bandwidth allocated to some task particles in the force-field F_T during the execution of the GPDA algorithm, each task particle corresponding to a VPC in ATM networks. Simulation parameters are the same as Fig.2.

• *Three performance criteria:* In order to evaluate the performance of optimization algorithms, we use the three criteria: the bandwidth allocation fairness FN, the resource utilization rate RUR for network links, and the users' satisfactory degree USD for network VPCs.

• *Influence of dynamical parameters:* The relation of the parameter ϵ in Eqs. $(5), (6)$ with respect to optimization performance of GPDA is shown in Fig.9.

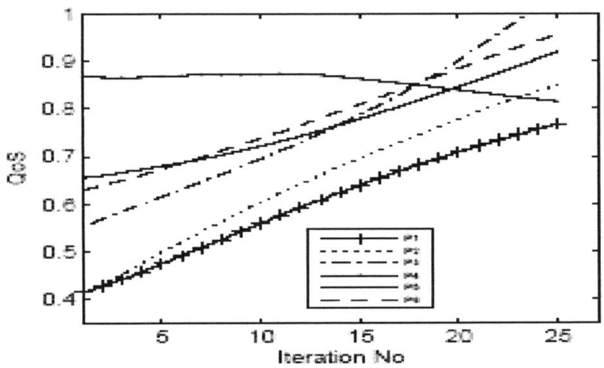


Fig. 8. The transients of $Q \circ S$ index obtained by some task particles in the force-field F_T during the execution of the GPDA algorithm, each task particle corresponding to a VPC in ATM networks. Simulation parameters are the same as Fig.2.

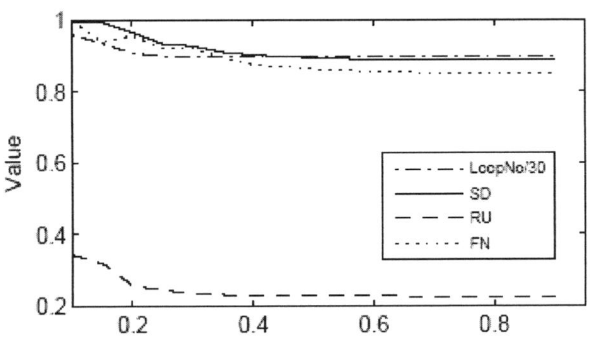


Fig. 9. The influence of the parameter ϵ in Eqs. $(5), (6)$ on the users' satisfactory degree (SD), resource utilization rate (RU), and the bandwidth fairness (FN). Simulation parameters are the same as Fig.2.

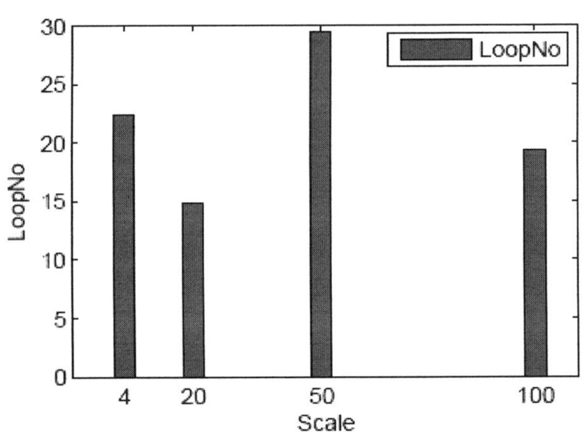


Fig. 10. The influence of the problem scale on the computational time. The values at horizontal coordinate represent the problem scales: $4 \times 4, 10 \times 20, 25 \times 50, 50 \times 100$. Other simulation parameters are the same as Fig.2.

• *The influence of problem size and demands on computational time of GPDA:* For different problem sizes and for different bandwidth demands and $Q \circ S$ requests, the computational time of the GPDA algorithm are shown in Fig.10, Fig.11 and Fig.12, respectively.

• *The influence of demands on the optimization performance:* For different bandwidth demands and $Q \circ S$, the optimization performance comparisons of the GPDA algorithm are shown in Fig.13 and Fig.14, respectively.

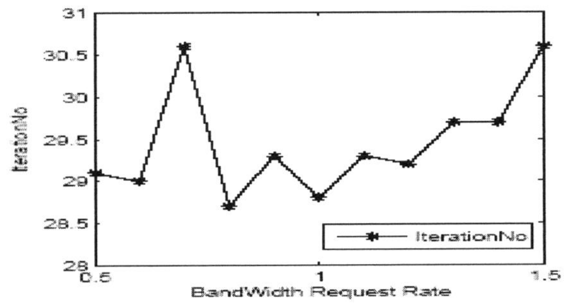


Fig. 11. The influence of total bandwidth demands on the computational time of the GPDA algorithm, where the bandwidth request rate represents the ratio of total bandwidth demands with respect to total bandwidth capacity of links. Simulation parameters are the same as Fig.2.

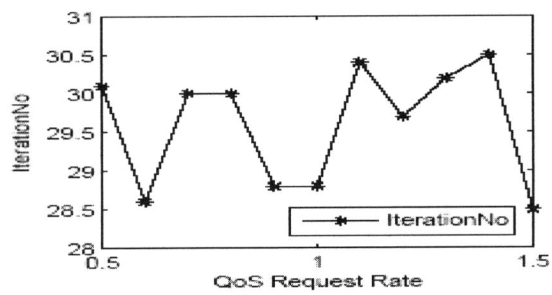


Fig. 12. The influence of total required $Q \circ S$ indexes of VPCs on the computational time of the GPDA algorithm, where the $Q \circ S$ request rate represents the ratio of total required $Q \circ S$ indexes with respect to total possible $Q \circ S$ indexes of links. Simulation parameters are the same as Fig.2.

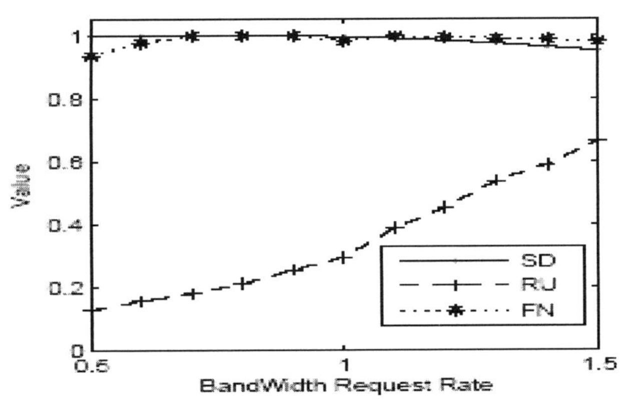


Fig. 13. The influence of total bandwidth demands on the users' satisfactory degree (SD), resource utilization rate (RU), and the bandwidth fairness (FN) for the GPDA algorithm, where the bandwidth request rate represents the ratio of total bandwidth demands with respect to total bandwidth capacity of links. Simulation parameters are the same as Fig.2.

• *Comparisons :* The comparisons between the algorithm GPMA and the Kelly's algorithm in [2]-[8] are shown in Fig.15, which demonstrate that for different problem sizes, the GPDA algorithm exhibits better performance than the

Kelly's algorithm in terms of the resource utilization rate, users' satisfactory degree and the allocation fairness.

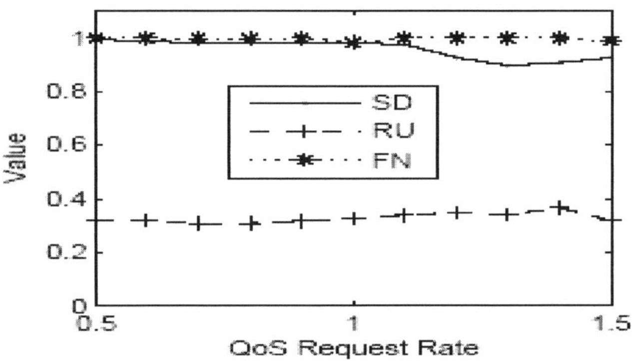


Fig. 14. The influence of total $Q \circ S$ indexes of VPCs on on the users' satisfactory degree (SD), resource utilization rate (RU), and the bandwidth fairness (FN) for the GPDA algorithm, where the $Q \circ S$ request rate represents the ratio of total required $Q \circ S$ indexes with respect to total possible $Q \circ S$ indexes of links. Simulation parameters are the same as Fig.2.

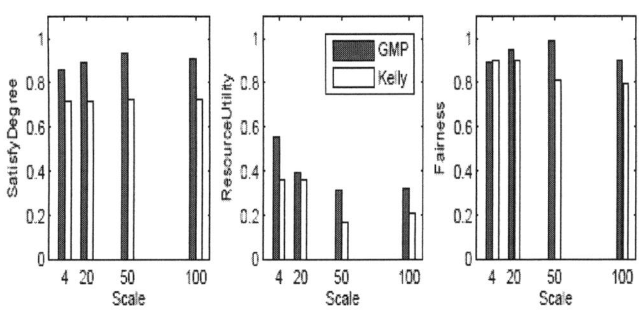


Fig. 15. Comparisons between the GPDA algorithm and the Kelly's algorithm in terms of the users' satisfactory degree (SD), resource utilization rate (RU), and the bandwidth fairness (FN) for different problem scales. Simulation parameters are the same as Fig.2.

V. Conclusions

This paper proposes a new generalized particle approach (GPDA) for parallel and distributed problem-solving in MAS. The GPDA-based algorithm and its properties are given. GPDA may deal with multi-type interactions, multi-degree autonomy, multi-objective optimization, multi-granularity coalition, and some random events occurring in MAS. The proposed generalized particle approach also has the advantages in terms of parallelism and feasibility for hardware implementation by VLSI technology.

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