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Performance evaluation of an intelligent CAC and routing framework for multimedia applications in broadband networks

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Abstract

In order to support multimedia communication, it is necessary to develop routing algorithms which use for routing more than one QoS parameters. This is because new services such as video on demand and remote meeting systems require better QoS. Also, for the Call Admission Control (CAC) of multimedia applications different QoS parameters should be considered. In our previous work, we proposed an intelligent routing and CAC strategy using cooperative agents. However, we only considered the time delay for the routing. The QoS and Congestion Control (CC) parameters were considered as indicators of QoS satisfication and congestion. In this work, we extend our previous work by proposing and implementing new algorithms based on Fuzzy Logic (FL) and Genetic Algorithm (GA) which use for CAC and routing many QoS parameters. The simulation results show that proposed framework has a good performance and is a promising method for QoS routing and CAC decision.

Keywords: Genetic algorithms; Fuzzy logic; Cooperative agents; Large-scale networks; Broadband networks; Multimedia applications

1. Introduction

The networks of today are going through a rapid evolution and they are expected to support a wide range of multimedia applications. The requirement for timely delivery of multimedia data raises new challenges for the next generation broadband networks. The key issue is the Quality of Service (QoS) routing [1–3]. Also, ensuring the QoS demands to traffic flows and groups of flows is an important challenge for future broadband networks, and resource provisioning via Call Admission Control (CAC) is a key mechanism for achieving this [4,5].

The purpose of admission control is to support the QoS demands of real time applications via resource reservation. The purpose of QoS routing is to find good paths which satisfy user requirements. To cope with broadband networks

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the CAC schemes and routing algorithms should give a fast decision and must be adaptive, flexible, and intelligent for efficient network management [6,7].

Use of intelligent algorithms based on Fuzzy Logic (FL), Genetic Algorithms (GA) and Neural Networks (NN) can prove to be efficient for telecommunication networks [8–12]. In our previous work, we proposed an intelligent CAC and routing framework using cooperative agents [11]. The proposed framework is based on Distributed Artificial Intelligence (DAI) approach, which deals with design of artificial agents to develop intelligent systems. We introduced two types of agents: simple and intelligent agents. The intelligent agents were based on FL and GA.

Considering our previous work on CAC, we proposed a Fuzzy Admission Control (FAC) scheme and a Fuzzy Equivalent Capacity Estimator (FECE). In the FAC scheme, we considered only two indicators for QoS and Congestion Control (CC). However, for multimedia applications more QoS and CC parameters should be considered. In this paper, we extend our previous work by proposing two additional schemes: Fuzzy QoS Controller (FQC) and Fuzzy Congestion Controller (FCC), which are integrated in the previous scheme. The new scheme is called Fuzzy Admission Control for Multimedia applications (MFAC).

Also, in the GA-based routing algorithm we considered only time delay as the only parameter for routing [9–11]. However, in order to support multimedia communication over broadband networks, it is necessary to develop routing algorithms which use for routing more than one QoS parameter such as throughput, delay, and loss probability [12]. This is because new services such as video on demand and remote meeting systems require better QoS. But, the problem of QoS routing is difficult due to the following reasons. The distributed applications have very diverse QoS constraints on delay, loss ratio, bandwidth, etc. Multiple constraints often make the routing problem intractable. For example, finding a feasible route with two independent path constraints is NP-complete [1].

In [12], we proposed a GA based routing algorithm which uses two QoS parameters for routing. This method called ARGAQ could support two QoS parameters: delay and transmission success rate. The simulation results show that ARGAQ method has better performance than a routing algorithm with only one QoS parameter called ARGA method. However, the ARGAQ method is effective only if the parameters have a relation between them and the GA fitness function can be expressed by a mathematical formula. In this work, we propose a new GA-based multi-objective optimization algorithm for QoS routing.

The paper is organized as follows. In Section 2, we give GA cycle and a brief introduction of FL. In Section 3, we introduce the previous work. The proposed framework is presented in Section 4. The simulation results are discussed in Section 5. Finally, conclusions are given in Section 6.

2. Intelligent algorithms

In this section, we give a short description of GA and FL.

2.1. GA cycle

GAs are search methods used to solve optimization problems. The GA mechanism is based on the interaction between individuals and the natural environment. GA comprises a set of individuals (population) and a set of biologically inspired operators (genetic operators). The individuals have genes which are the potential solutions for a problem. The genetic operators are crossover and mutation. GA generates a sequence of populations by using genetic operators among individuals. Only the most suited individuals in a population can survive and generate offsprings, thus transmitting their biological heredity to new generations [13,14].

The GA cycle is shown in Fig. 1. At the beginning, an initial population of potential solutions is created as a starting point for the search. In the next stage, the performance (fitness) of each individual is evaluated with respect to the constraints imposed by the problem. Based on each individual's fitness, a selection mechanism chooses "parents" for the crossover and mutation operators. The crossover operator takes two chromosomes and swaps part of their genetic information to produce new chromosomes. The mutation operator introduces new genetic structures in the population by randomly modifying some of genes, helping the search algorithm to escape from local minimum. The offspring produced by the genetic manipulation process are the next population to be evaluated. GA can replace either a whole population or just its less fit members. The creation–evaluation–selection–manipulation cycle repeats until a satisfactory solution to the problem is found, or some other termination criteria are met.

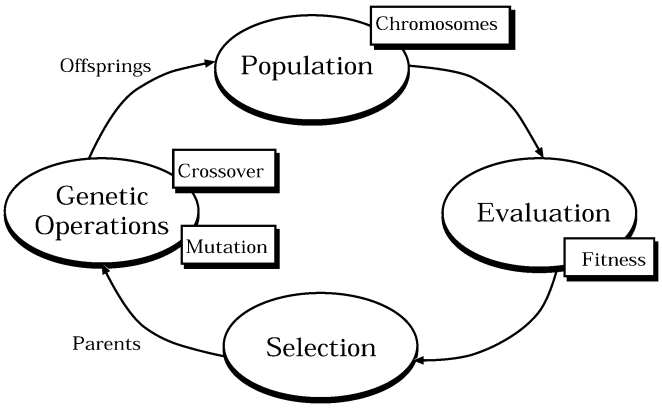

Fig. 1. GA cycle.

2.2. FL

The concept of a fuzzy set deals with the representation of classes whose boundaries are not determined. It uses a characteristic function, taking values usually in the interval [0, 1]. The fuzzy sets are used for representing linguistical labels. This can be viewed as expressing an uncertainty about the clear–cut meaning of the label. But important point is that the valuation set is supposed to be common to the various linguistic labels that are involved in the given problem [15].

The fuzzy set theory uses the membership function to encode a preference among the possible interpretations of the corresponding label. A fuzzy set can be defined by examplification, ranking elements according to their typicality with respect to the concept underlying the fuzzy set. The prototypical element receives the greater membership grade. Fuzzy set naturally appears in non-strict specification. It may be soft constraints or flexible requirements for which slight violations can be tolerated (e.g., the dead line is today, but tomorrow is still acceptable although less good), or elastic classes of objects, approximate descriptions of types of situation to which a given procedure can be applied, or even procedures with fuzzy stated instructions. The ability of fuzzy sets to model gradual properties or soft constraints whose satisfaction is matter of degree, as well as information pervaded with imprecision and uncertainty, makes them useful in a great variety of applications. The most popular area of application is fuzzy control. In fuzzy control systems, expert knowledge is encoded in the form of fuzzy rules, which describe recommended actions for different classes of situations represented by fuzzy sets. An interpolation mechanism provided by the fuzzy control methodology is then at work. A fuzzy control unit can do the same work as a Proportional Integral Differential (PID) controller, since it implicitly defines a numerical function tying the control variables and the observed control variables together. However, by PID controllers only linear control laws can be attained, while the FL controller may capture non-liner laws, which may explain the success of the FL controllers over PID controllers. In fact, any kind of control law can be modeled by the FL control methodology, provided that this law is expressible in terms of "if ... then ..." rules, just like in the case of expert systems. However, FL diverges from the standard expert system approach by providing an interpolation mechanism from several rules. In the contents of complex processes, it may turn out to be more practical to get knowledge from an expert operator than to calculate an optimal control, due to modeling costs or because a model is out of reach [15].

3. Previous work

3.1. Distributed network architecture

The proposed network architecture is a Multi-Agent System (MAS). The agents are distributed and cooperate together. Each Domain Management Agent (DMA) has four agents: Resource Management Agent (RMA), Pre-computation Agent (PA) which includes Search Space Reduction Agent (SSRA) and Tree Model Network Agent (TMNA), Destination Discovery Agent (DDA), and Routing Agent (RA) with its Intra Domain (IntraD) and Inter Domain (InterD) agents. The DMA structure is shown in Fig. 2. The PA includes SSRA and TMNA. We call these

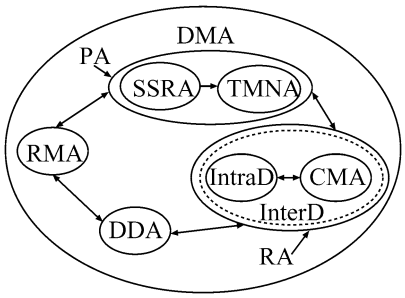

Fig. 2. DMA structure.

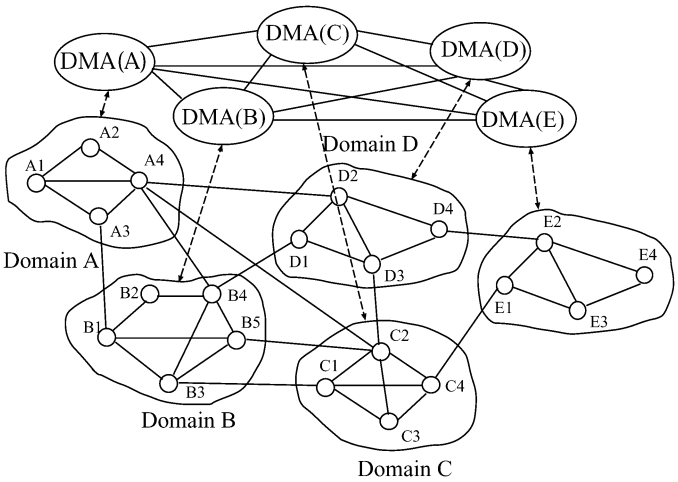

Fig. 3. Distributed network architecture with DMAs.

two agents PA, because they make the computation before the RA is activated. The computation time starts when a new connection makes a request to the network. The RA has the IntraD and InterD agents. In fact, the InterD agent is a composition of IntraD agent and Connectivity Management Agent (CMA), which are activated by an escalation strategy. The distributed network architecture with DMAs is shown in Fig. 3. This architecture can be considered as a hierarchical architecture, where in first level are domains and in the second level are DMAs. We have shown here only five domains. But, this architecture can be scaled-up easily by increasing the number of DMAs and domains in order to deal with the increasing users demands and number of switches.

3.2. RMA

In difference from the equivalent capacity admission control method [16], which uses only the available capacity as the only variable for the call admission decision, our FAC scheme considers four parameters: Quality of service (*Qs*), Network congestion parameter (*Nc*), Available capacity (*Ac*), and user requirement parameter which is expressed by Equivalent capacity (*Ec*). By simulations, we found that two membership functions are enough for *Qs*, *Nc*, *Ac* linguistic parameters, and three membership functions are enough for *Ec* linguistic parameter. The output linguistic parameter is the Acceptance decision (*Ad*). In order to have a soft admission decision, not only "accept" and "reject" but also "weak accept," "weak reject," and "not accept not reject" are used to describe the accept/reject decision [17]. The membership functions are shown in Fig. 4, the FAC scheme is shown in Fig. 5 and the Fuzzy Rule Base (FRB) is shown in Table 1.

The information for FAC are given by Bandwidth Management Predictor (BMP); Congestion Information Indicator (CII); Quality of Service Indicator (QSI); and Equivalent Capacity Estimator (ECE). The BMP works in this way: if a connection is accepted, the connection bandwidth is subtracted from the available capacity of the network, otherwise, if a connection is released, the connection bandwidth is added to the available capacity of the network. The CII decides

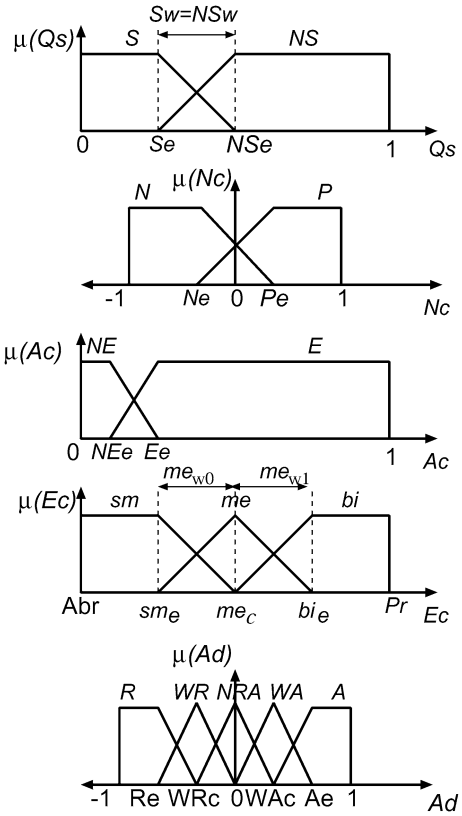

Fig. 4. FAC membership functions.

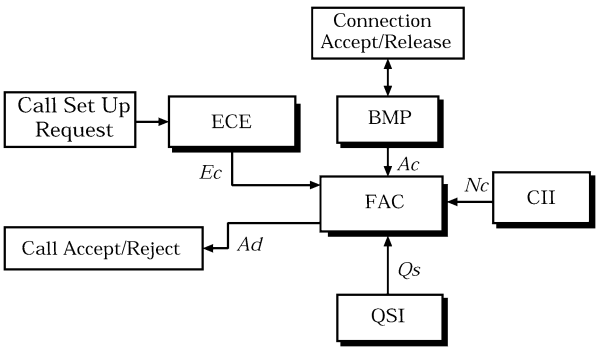

Fig. 5. FAC scheme.

whether the network is or is not congested. The QSI determines whether allowing a new connection violates or not the QoS guarantee of the existing connections.

In order to get a better estimation of *Ec*, we proposed a Fuzzy ECE (FECE) scheme [18]. But, for the sake of the space, we will not explain here.

3.3. PA and DDA

3.3.1. SSRA

The flowchart of SSRA is shown in Fig. 6. The key element of SSRA is Effective Topology (ET) extraction. The ET extraction of a network is defined as the topology based on which a path is constructed for a connection. In order to extract the ET, the network connectivity information, link and node metrics, and QoS requirement of the new

Table 1
FRB

Rule	*Qs*	*Nc*	*Ac*	*Ec*	*Ad*
0	S	N	NE	sm	NRA
1	S	N	NE	me	WR
2	S	N	NE	bi	WR
3	S	N	E	sm	WA
4	S	N	E	me	NRA
5	S	N	E	bi	WR
6	S	P	NE	sm	WA
7	S	P	NE	me	NRA
8	S	P	NE	bi	WR
9	S	P	E	sm	A
10	S	P	E	me	A
11	S	P	E	bi	A
12	NS	N	NE	sm	R
13	NS	N	NE	me	R
14	NS	N	NE	bi	R
15	NS	N	E	sm	NRA
16	NS	N	E	me	NRA
17	NS	N	E	bi	R
18	NS	P	NE	sm	WR
19	NS	P	NE	me	R
20	NS	P	NE	bi	R
21	NS	P	E	sm	NRA
22	NS	P	E	me	NRA
23	NS	P	E	bi	WR

connection are required. We use the *Ec* predicted by FECE to specify the QoS demand of a new connection. In order to have a low overhead processing time, we consider the Available Bandwidth (AB) as the only link and node metrics. If a Link Available Bandwidth (LAB) or Node Available Bandwidth (NAB) is less than *Ec* of a connection, this means that every path which passes via this link or node cannot satisfy the connection requirements.

First, the SSRA based on the required *Ec* checks all links in the network whether their AB satisfies or not the *Ec*. If a LAB does not satisfy the *Ec* then the link is excluded from ET. Otherwise, the link is included in the ET and the next link is checked. The procedure is repeated until all links are finished. Next, the SSRA checks all nodes in the network, whether their AB satisfies the *Ec* or not. If the NAB does not satisfy the *Ec* then the node is excluded from the ET. Otherwise, the node is included in the ET and the next node is checked. The procedure is repeated until all nodes are finished. Finally, after all links and nodes are checked, the network ET is constructed and the complete procedure is finished.

By using the SSRA, a network with many nodes and links will be reduced in a network with a small number of nodes and links. Thus, the proposed framework is able to cope with more large-scale networks.

3.3.2. TMNA

After the execution of SSRA, the ET of the network is transformed in a tree model by TMNA. To explain this procedure, a small network with 8 nodes as shown in Fig. 7 is considered. Node A is the Source Node (SN) and node H is the Destination Node (DN). All paths are expressed by the tree model shown in Fig. 8. In the shaded areas are shown the same paths from node C to H. Therefore, we further reduce the tree network as shown in Fig. 9. The tree model constructed by TMNA is used by IntraD agent for intra-domain routing. In the reduced tree model, each tree junction is considered as a gene and the path is represented by the chromosome.

3.3.3. DDA

After a new connection is accepted, the RMA sends a request to the DDA. The DDA consults a table with node name entries to check whether SN and DN are in the same domain or not. If SN and DN are in the same domain, the DDA of the source domain activates the IntraD agent. Otherwise, if the SN and DN are in different domains, the InterD agent is activated.

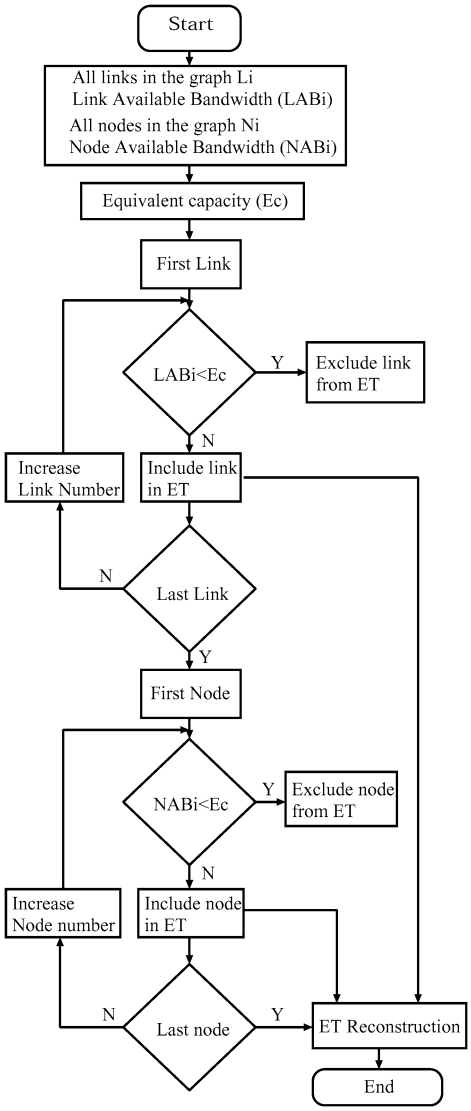

Fig. 6. SSRA flowchart.

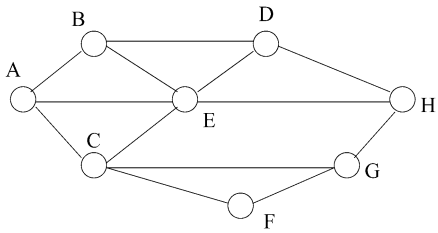

Fig. 7. A network example with 8 nodes.

3.4. IntraD agent

The IntraD algorithm is a delay-constraint unicast source routing mechanism and is based on GA. The most important factor to achieve efficient genetic operations is gene coding. In the Genetic Load Balancing Routing (GLBR) algorithm [8], the genes are put in a chromosome in the same order the nodes are in a path so the chromosomes have

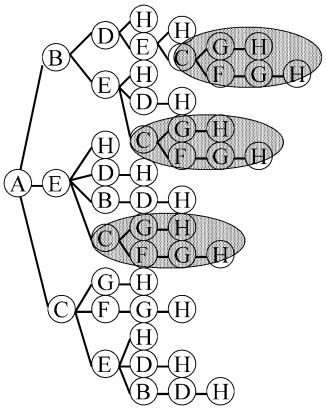

Fig. 8. Network tree model.

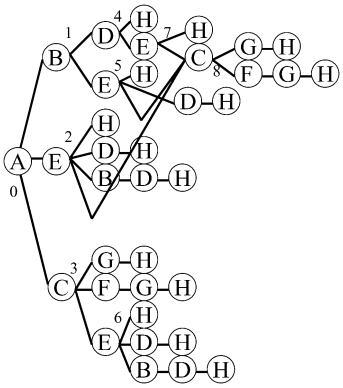

Fig. 9. Reduced network tree model.

different sizes which result in complex crossover operation. In order to simplify the genetic operations of GLBR, in the IntraD algorithm, the network is expressed by a tree network and the genes represent the tree junctions. The genes in a chromosome have two states "active" and "inactive." A gene is called "active" if the junction is in the path, otherwise the gene is in "inactive" state. The genetic operations are carried out in the "active" genes. Each gene includes information of the adjacent nodes. The paths are represented by chromosomes which have the same length. Therefore, the crossover operation becomes easy.

3.5. InterD agent

After the DDA finds out that SN and DN are in different domains, the InterD agent is activated. The InterD agent is a composition of IntraD agent and CMA. It uses an escalation strategy to make the inter-domain routing. By using the escalation strategy, the information exchange is needed only in domains where the selected path passes. Thus, the information flooding in all domains is not necessary and the network resources can be use efficiently. The InterD agent operates in the following way. After receiving a connection request, a node become a SN. The IntraD agent finds a path inside the domain. The DN of the source domain starts the CMA. The CMA is a simple agent. It finds the best link by using a sorting algorithm based on the inter-domain links parameters. After the CMA decides the best link for connection, the DN of this link becomes a SN and the IntraD agent is activated in the following domain. This procedure is escalated until the DN of the destination domain is found.

4. Proposed method

In this section, we present the proposed MAFC scheme and multi-objective optimization method.

4.1. Proposed MFAC scheme

In our previous work, we considered only two indicators for QoS and CC. However, for multimedia applications more QoS and CC parameters should be considered [19]. For this reason, in this paper we design two fuzzy based controllers: FQC and FCC. The scheme of proposed MFAC is shown in Fig. 10.

4.1.1. FQC

As input linguistic parameters for FQC, we consider the throughput Th, the delay D, and the loss probability Lp. The membership functions for FQC are shown in Fig. 11. The term sets of Th, D, and Lp are defined respectively as:

$$T(Th) = \{Small, Medium, Large\} = \{Sa, Mu, Lr\};$$

$$T(D) = \{Low, Middle, High\} = \{Lo, Mi, Hi\};$$

$$T(Lp) = \{Low, Normal, High\} = \{Lw, Nr, Hg\}.$$

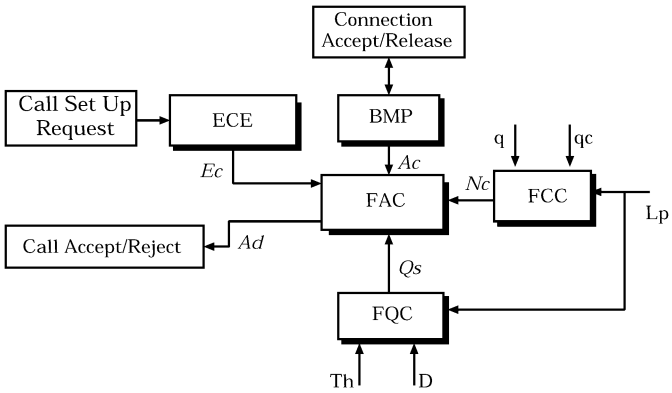

Fig. 10. Proposed MFAC scheme.

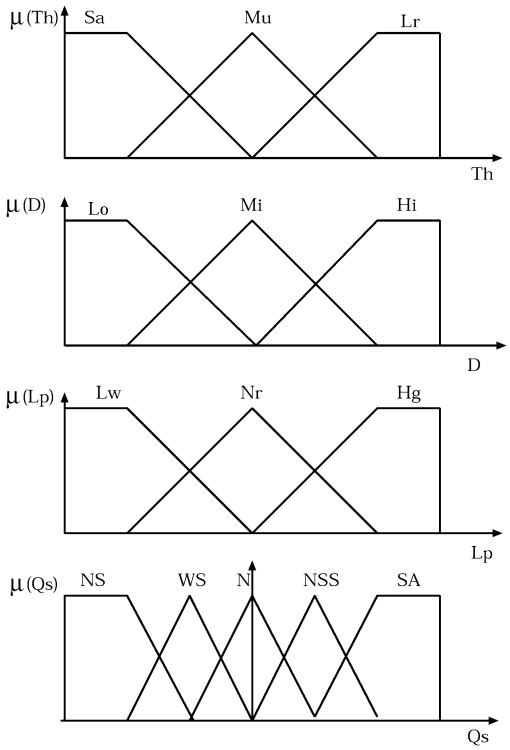

Fig. 11. FQC membership functions.

From our experience and many simulations, we decided that three membership functions are enough for *Th* linguistic parameter, three membership functions are enough for *D* linguistic parameter, and two membership functions are enough for *Lp* linguistic parameter.

The term set of the output linguistic parameter $T(Qs)$ is defined as {Not Satisfied, Weak Satisfied, Normal, Not So Satisfied, Satisfied}. We write for short as {NS, WS, N, NSS, SA}.

4.1.2. FCC

For FCC, as input linguistic parameters, we consider the queue length *Ql*, the queue length change rate *Qcr*, and the loss probability *Lp*. The membership functions for FQC are shown in Fig. 12. The term sets of *Ql*, *Qcr*, and *Lp* are defined respectively as:

$$T(Ql) = \{Empty, Middle, Full\} = \{E, Mi, Fu\};$$

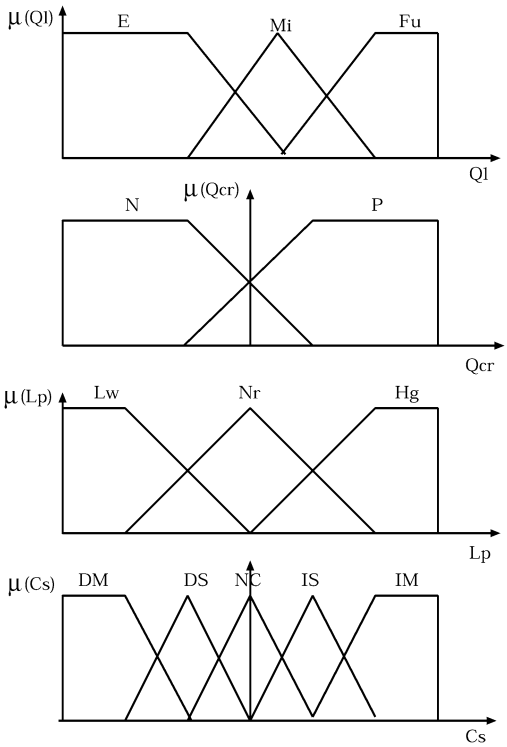

Fig. 12. FCC membership functions.

$$T(Qcr) = \{Negative, Positive\} = \{Ne, Po\};$$
$$T(Lp) = \{Low, Normal, High\} = \{Lw, Nr, Hg\}.$$

Usually for congestion control is used a two threshold congestion method. In this method the system is considered congested if the queue length exceeds the high threshold and uncongested if the queue length drops below the low threshold. For this reason, the maximum value of Ql would be the total buffer size. The edges of the membership functions can be the low and high threshold. For the Qcr linguistic parameter the maximum positive and negative queue length change would be the queue length. For the Lp linguistic parameter, the values for "Low," "Normal" and "High" can be decided considering the required QoS.

The term set of the output linguistic parameter $T(Cs)$ is defined as {Decrease More, Decrease Slightly, No Congestion, Increase Slightly, Increase More}. We write for short as {DM, DS, NC, IS, IM}.

4.2. Multi-objective optimization

The proposed method uses the multi-division group model for multi-objective optimization [20]. When a purpose function can be divided in different purpose functions, the global domain can be divided in different domains and each individual can evolve in its domain. The method finds a route if the individual satisfies the end conditions. In this case the individual is selected as the optimized route. If an optimal route cannot be found, then the best individuals are traded-off between each domain. This procedure is carried out until the number of generations is achieved. The procedure is shown in Fig. 13. As shown in the figure, four different purpose functions are independent from each other and each process is operating independently in each domain.

In Fig. 14 is shown an example of Delay Time (DT) and Communication Cost (CC). The vertical axis shows the DT and horizontal axis the CC. The DT and CC have trade-off relations. The points in the figure show the individuals (routes). The individuals which are in the left-upper part of the figure have the lowest CC. On the other hand, the individuals which are in the right-lower part of the figure have the lowest DT values. The individuals which are in the

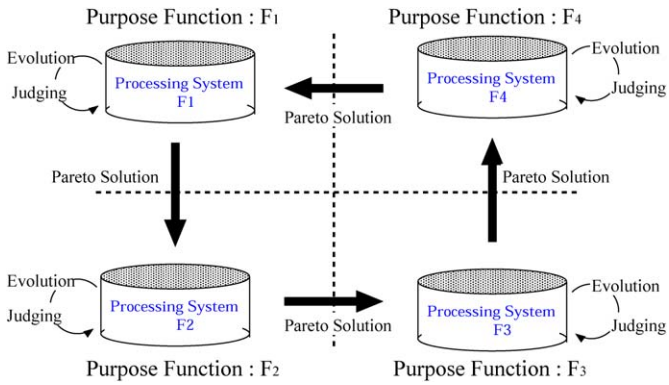

Fig. 13. Multi-objective optimization.

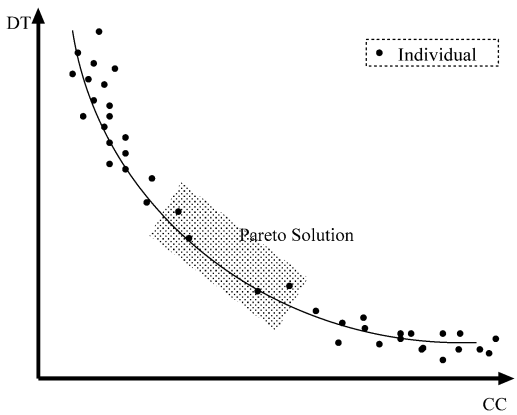

Fig. 14. Pareto solution for DT and CC.

shaded area have good values for both DT and CC. The shaded area is called "Pareto solution". The individuals near Pareto solution can be found by exchanging the solutions of different domains.

4.2.1. QoS routing search engine

The structure of Routing Search Engine (RSE) is shown in Fig. 15. It includes two search engines: Cache Search Engine (CSE) and Tree Search Engine (TSE). Both engines operate independently, but they cooperate together to update the route information. When the RSE receives a request for QoS routing from a client, it forwards the request in parallel to CSE and TSE. Then, the CSE and TSE search in parallel to find a route satisfying the required QoS. The CSE searches for a route in the cache database (in the cache database, the destination and route information is

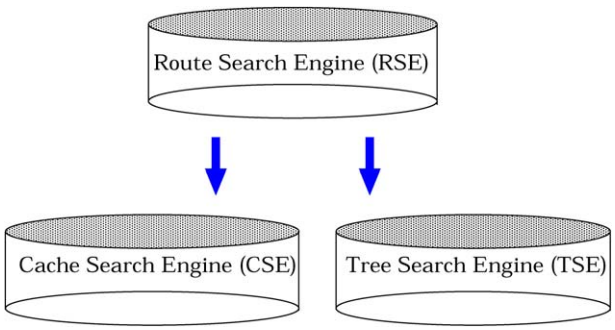

Fig. 15. RSE structure.

saved as a database item). If the found route by CSE satisfies the required QoS, this route information is sent to RSE, otherwise the route is put in the gene pool as new individual. If a QoS route cannot be found by CSE, the route found by TSE is sent to RSE. It should be noted that CSE is faster than TSE, because the TSE searches for all routes in its domain using a GA-based routing.

4.2.2. CSE-TSE cooperation and database updating

The database information should be updated because the network traffic and the network state change dynamically. In order to update the database, the CSE and TSE cooperate together. When the TSE finds a good QoS routing, it puts this route information in the cache database as shown in Fig. 16. The route information which is used frequently is given high priority, thus this route can be searched very fast by CSE. In the case when the CSE finds a route in the database, but this route does not fulfill the required QoS by client, this route information is put as a new individual in the genepool of TSE as shown in Fig. 17 and will be used as a new individual during the selection process of the GA.

The update information of database is shown in Fig. 18. After CSE finds a route in the database, it checks whether this route satisfies or not the required QoS. If the QoS is not fulfilled, then this route is deleted from the database. On the other hand, when the QoS is fulfilled, the route is given higher priority, thus it can be searched very fast during the next search.

4.2.3. TSE operation

When TSE receives an order from RSE to find a QoS route, it transforms the network in a tree network with the source node as the root of tree. After that, the tree network is reduced in the parts where are the same routes. By using the tree model, the routing loops can be avoid, therefore the algorithm does not lose searching time in the routing loops. Also, by reducing the tree network, the chromosome length is shorten so the genetic operations become simple.

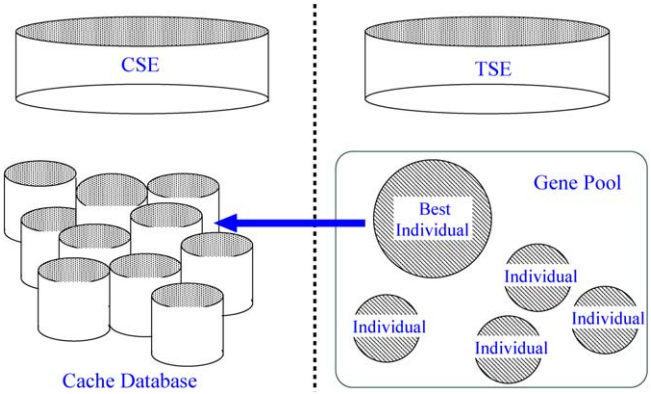

Fig. 16. CSE and TSE cooperation 1.

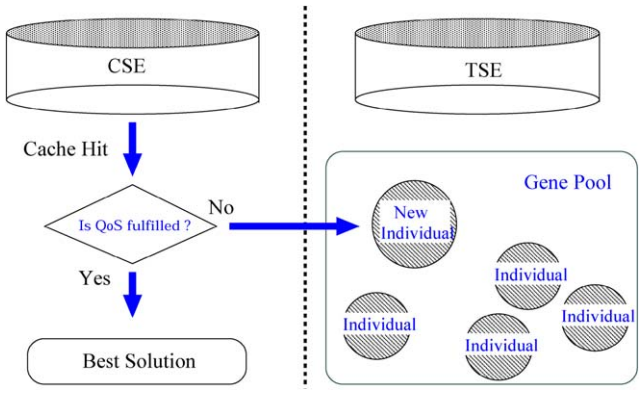

Fig. 17. CSE and TSE cooperation 2.

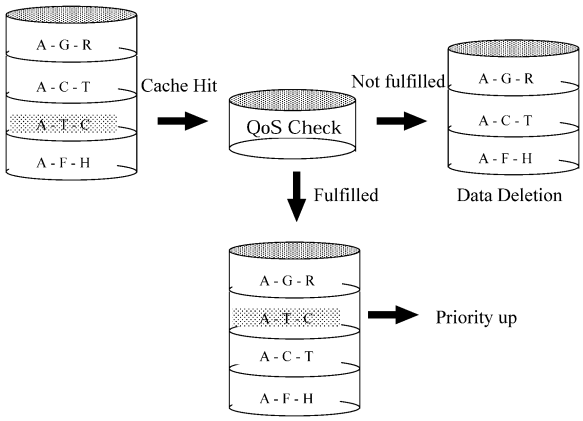

Fig. 18. Cache database update.

After the reduction of the tree network, the genes are represented by the junctions of the tree. The genes in a chromosome have the information of the adjacent nodes. Because, the individual and chromosome are the same, the route is represented by the chromosome and the population is a collection of routes.

After the gene coding, initial population is selected. In the selected population, the ranking selection model is used to select two individuals in order to carry out the genetic operation. The ranking model ranks each individual by their fitness. The rank is decided based on the fitness and the probability is decided based on the rank. The individual fitness is based on DT and CC values. The individuals which have small DT and CC have high fitness value.

The genetic operations are the crossover and mutation. As crossover operation is used the single point crossover, because a simple operation is needed to get a fast response. In the mutation operation, the genes are chosen randomly in the range from zero up to mutation probability $p\_mutation \leqslant \frac{1}{\ell}$, where l is the chromosome length.

After the crossover and mutation, the elitist model is used. Based on the elitist model the individual which has the highest fitness value in a population is left intact in the next generation. Therefore, the best value is always kept and the routing algorithm can converge very fast to the desired DT and CC values. The offsprings produced by the genetic operations are the next population to be evaluated. The genetic operations are repeated until a route satisfying the required DT and CC values is found or the initialized generation size is achieved.

5. Simulation results

5.1. Simulation results for RMA

The FAC and MFAC schemes use the same mechanism (FECE) for estimation of equivalent capacity. The new MFAC has the same properties as FAC but also has a better estimation of QoS and CC indicators. In following, we compare by simulations the performance of FECE with conventional methods such as fluid flow approximation and stationary approximation. The performance comparison between Guérin's method and our proposed approximation for $N = 50$ is shown in Fig. 19. At the beginning, both methods have the same behavior, because they use the stationary approximation. But, as the source utilization increases, our method makes a better estimation than Guérin's method. For $Su = 0.5$, our method and the exact value are very close. Otherwise, Guérin's method has a difference of about one order of magnitude compared with the exact value. For high source utilization, Guérin's method uses the flow approximation and the characteristic is approaching the exact value. However, our method shows a better performance even for high source utilization.

In order to compare the statistical multiplexing gain of methods, we consider a multiplexer which can process two classes of connections: class 1 and class 2. We consider that all connections in a class have the same traffic parameters $Pr = 4$ Mb/s, $Su = 0.4$, $Pbd = 0.106$ s, and $Pr = 10$ Mb/s, $Su = 0.4$, $Pbd = 0.021$ s, for class 1 and class 2, respectively. The admission regions for the buffer size 1000 cells are shown in Fig. 20. As the buffer size increases, the number of connections admitted into the network is increased. The FAC and MFAC schemes can admit more connections than equivalent capacity method, thus increasing the network utilization.

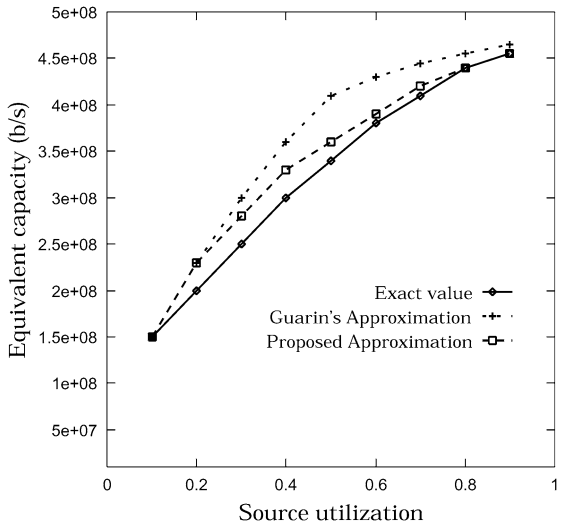

Fig. 19. Performance comparison between Guérin's method and FECE.

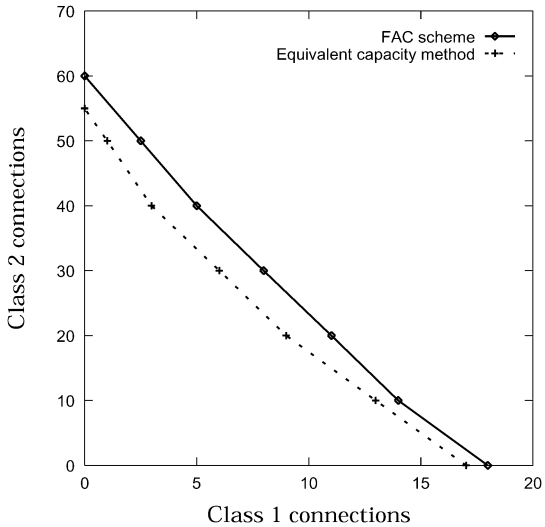

Fig. 20. Admission regions.

5.2. Simulation results for proposed routing algorithm

For the simulation, we use a network with 20 nodes. The network model is shown in Fig. 21. First, we set in a random way the DT and CC in each link of network. The RSE generates in random way the values of the required QoS and the destination node information. Next, the CSE and TSE search in parallel to find a route. If the CSE finds a route in the cache database it checks whether this route satisfies the QoS or not. If the found route satisfies the required QoS, this route is sent back to the RSE. Otherwise, the route is put as a new individual in the gene pool. If a QoS route cannot be found by CSE, the route found by TSE is sent to RSE. The genetic operations are repeated until a solution is found or the number of 200 generations is achieved. The selected route is put in the cache database. The CSE and TSE cooperate together to update the cache database.

In Table 2 are shown the simulation results using TSE. If there are few individuals in the population, the Generation Number (GN) which shows the number of generations needed to find a solution becomes large. On the other hand, when the number of individuals is high, the GN to find a solution becomes small. However, when the number of individuals is 12 and 16, the difference is very small. This is because some individuals become the same in the genepool. Considering the exchange of individuals between domains, it can be seen that when the exchange interval is short the solution can be found very fast. This shows that by exchanging the individuals the algorithm can approach very quickly to the Pareto solution.

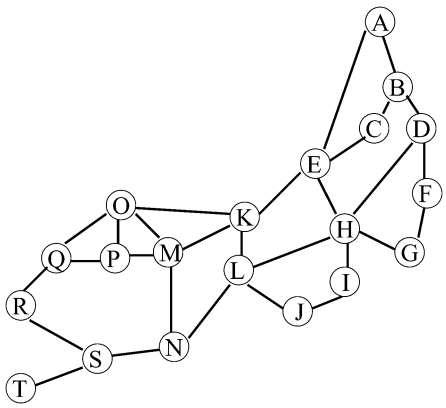

Fig. 21. Network model with 20 nodes.

Table 2
Time needed for one generation (ms)

Number of individuals	GN exchange			
	3	5	7	10
4	44.43	50.45	46.19	55.59
8	26.83	28.01	40.26	31.17
12	23.55	26.49	26.04	26.71
16	22.22	22.23	23.25	24.04

Table 3
GA-based routing algorithms comparison

Method	RP	GC	RS	AC	RSCM
GLBR	DT	Network nodes	Source	Low	Single metric
ARGA	DT	Tree junctions	Source	Low	Single metric
ARGAQ	DT, TSR	Tree junctions	Source	Middle	Single mixed metric
TSE	DT, CC	Tree junctions	Source	Middle	Multiple metrics

In following, we investigate the evolution of proposed algorithm in each domain. The number of individuals for one generation is 10 and the individuals are exchanging after 5 generations. In Fig. 22 is shown the genepool state for DT and in Fig. 23 for CC. The Delay 1 and Cost 1 show the starting genepool state for DT and CC, respectively. We checked the genepool state for every 5 generations when the individuals are exchanged between domains. But for the sake of the space, we show here only the genepool state after 5, 25, 55 and 70 generations. The number of individuals for each generation is 10, but it should be noted that after genetic operations the values of DT and CC may go out of the values shown in these figures. Thus some individuals are not shown. The values of the QoS required from the client are less than 250 and 400 for DT and CC, respectively. The best value for DT and CC are in the left-down part of the figures. It can be seen that the individuals are approaching that part when the number of generations is increased. When the number of generations is 70, the values of one individual in the left-down part of the figures are less than 250 and 400, for DT and CC, respectively.

In Table 3 is shown the comparison between GA-based routing algorithms. The GLBR and ARGA use as the Routing Parameter (RP) DT, ARGAQ uses DT and TSR, and TSE uses DT and CC. The GLBR uses for Gene Coding (GC) the nodes of network, while ARGA, ARGAQ and TSE uses the tree junctions. By using the network nodes as gene, the GLBR may enter in routing loops. Also, the searched route may not exist, so the algorithm after searching a route should check whether the route exist or not. If the searched route does not exist, the GLBR should search for another route. Thus, the searching time increases. Three other methods by using as gene the tree junction can avoid the routing loops and always the route exist. So there is not need to check the route existence. All four methods use as Routing Strategy (RS) the source routing thus they are considered source-based routing methods. Considering the algorithm complexity, the GLBR and ARGA have a low complexity, because they use only one parameter for routing. The complexity of ARGAQ and TSE is higher than GLBR and ARGA methods.

The last comparison is about the Routing Selection Criterion Metrics (RSCM). The GLBR and ARGA use single metrics (DT). Thus, they cannot be used for QoS routing. The ARGAQ uses a single mixed metrics (T), which is the ratio of DT and TSR. By using the single mixed metric, the ARGAQ can only be used as an indicator because it does not contain sufficient information to decide whether user QoS requirements can be met or not. Another problem with ARGAQ has to do with mixing of parameters of different composition rules, because may be not simple composition rule at all. The TSE uses multiple metrics for route selection. It should be noted that problem in QoS routing is much more complicated since the resource requirements specified by the applications are often diverse and application-dependent. In the proposed method, the DT and CC have trade-off relation and to get the composition rule the TSE use Pareto solution method. In this paper, we used only two parameters for QoS routing. However, the TSE in different from ARGAQ can use for routing multiple QoS metrics. Another merit of TSE is that it works and cooperates with CSE and thus if a good QoS route selected by TSE has a higher priority in the cache database it can be found very fast in the next search.

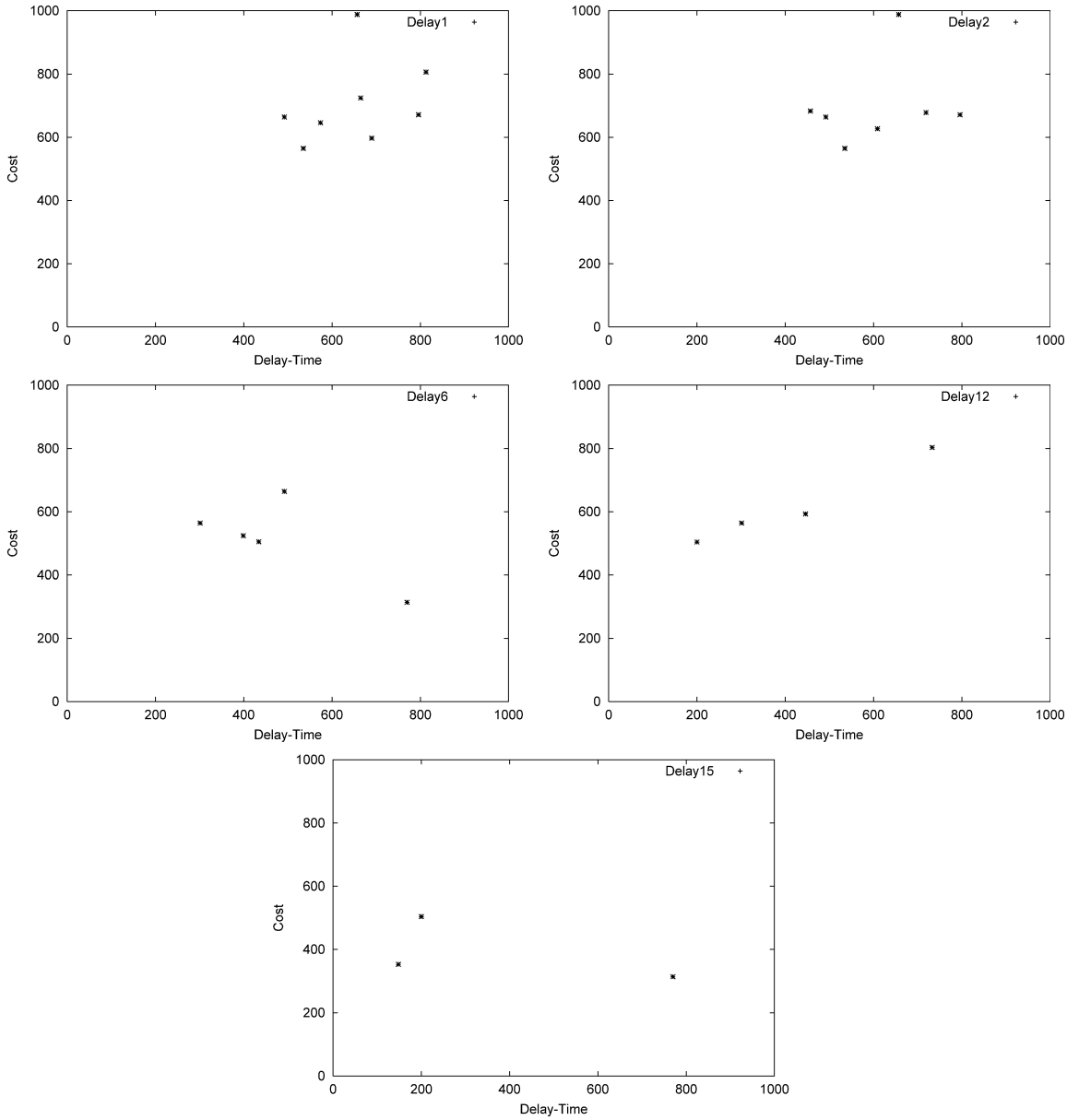

Fig. 22. Genepool state for DT.

6. Conclusions

In this paper, we proposed and evaluated an intelligent CAC and routing framework for broadband networks which is based on FL and GA. We evaluated the proposed framework by simulations.

From the simulation results, we conclude as follows.

- MFAC has the same features as FAC, but better decision for QSI and CII.
- Our proposed approximation method has a good *Ec* estimation compared with conventional methods.
- FAC and MFAC schemes have a better admission region than the equivalent capacity method.
- The proposed routing method is a flexible and adaptive source routing method.
- When there are few individuals in the population, the GN becomes large.

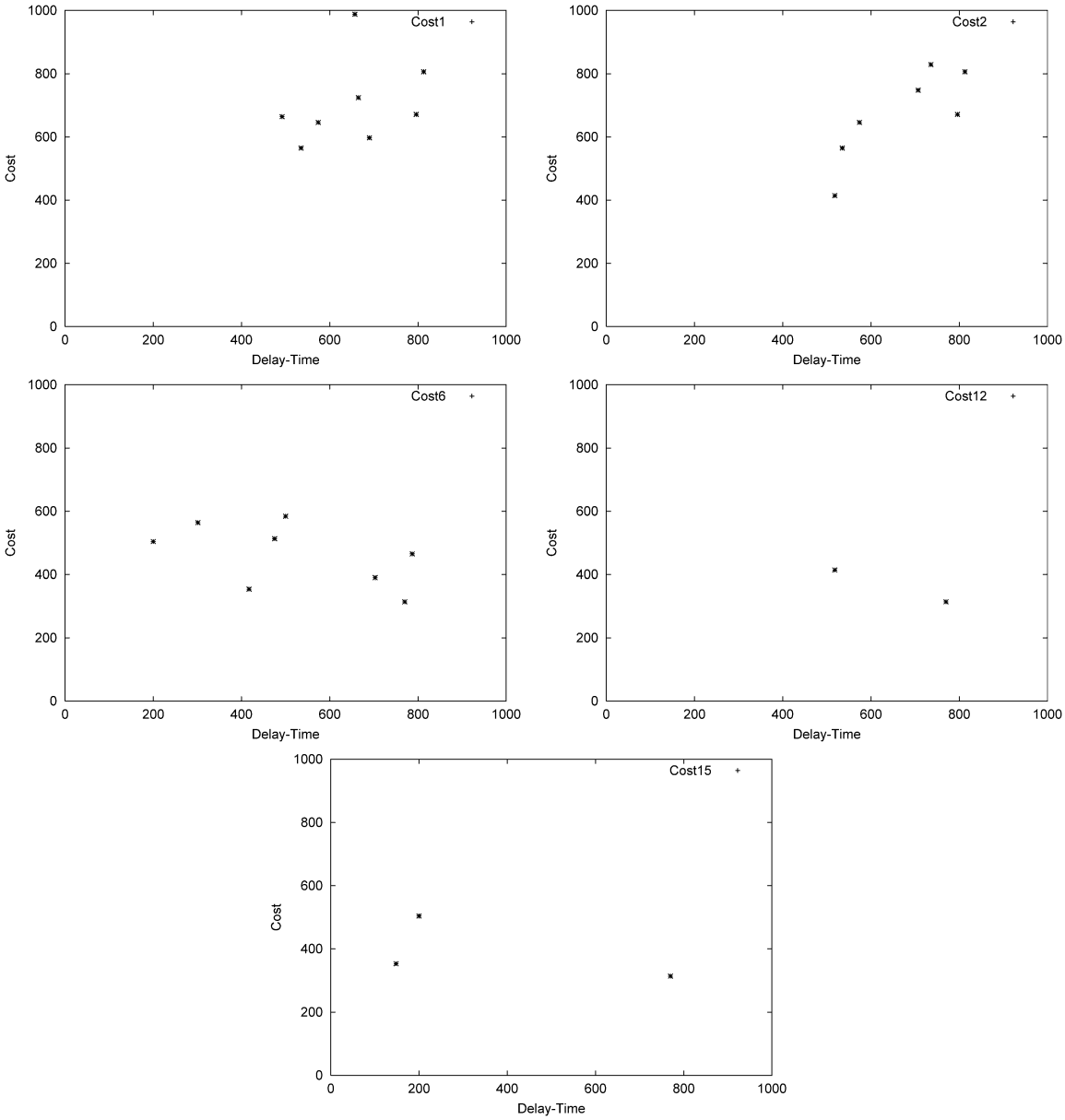

Fig. 23. Genepool state for CC.

- When the exchange interval of individuals is short the solution can be found very fast and the algorithm can approach very quickly to the Pareto solution.
- The proposed method can support QoS routing for multiple metrics.

In this paper, we carried out the simulations of RA only for two QoS metrics. In the future, we would like to extend our study to use more QoS metrics for routing. Also, we plan to make an overall performance evaluation of the proposed MFAC scheme.

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