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An Improvement in Window-based Protocols using Evolutionary Multi-objective Optimization

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Abstract- Evolutionary multiobjective optimization (EMO) optimizes multi-objectives, conflicting with each other, simultaneously. In this paper, EMO has been utilized to improve a window based protocol based on two parameters, Bandwidth Delay Product (BDP) and end-to-end delay. The problem has been simulated using gamultiobj tool in the MATLAB.

Index Terms- Evolutionary Multiobjective Optimization (EMO); Bandwidth Delay Product (BDP); Transmission Control Protocol (TCP); end-to-end delay.

I. Introduction

Multiobjective optimization is a problem of optimizing a number of objectives simultaneously which results into a set of solutions called Pareto optimal set. This set can be derived using evolutionary algorithms. Thus Evolutionary Multiobjective Optimization (EMO) is providing significant results in all domains.[1].

EMOs are applicable in handling routing problems in various types of networks. In [2] the EMO concepts have been utilized in routing for wireless ad-hoc networks. In this Pareto optimal sets are generated with the parameters Delay, robustness and energy in a sensor network. For the optimization of four QoS parameters bandwidth constraints, delay, traffic and number of hops in MANET (Mobile ad-Hoc Network), the Multiobjective Genetic algorithms have been used in [3]. A new algorithm for multicast routing has been proposed in [4] which solve GMM models for dynamic Multicast Groups which is named as Multi-tree Multiobjective Multicast routing algorithm (M-MMA).

In [5,6]A Fuzzy Multi-objective routing algorithm has been proposed in B-ISDN (Broadband Integrated Services Digital Network). The problem has been modeled in fuzzy multiobjective formulation. Multiple design objectives of the embedded systems are handled with multiobjective approach in [7] for the purpose of optimizing routing and topology. In [8] a shortest path routing problem in a computer network has been solved using a Multiobjective Strength Pareto Evolutionary Approach (SPEA). In a Wireless Mesh Network (WMN), the routing and QoS problem has been solved using multiobjective optimization in [9]. The parameters utilized are bandwidth, packet loss rate, delay and power consumption.

In window based protocols, sender keeps transmitting the packets equal to the size of window before waiting for first acknowledgement from the receiver. Ideally, these protocols give best throughput when pipe is filled with the packets. To ensure this, we need to have maximum possible bandwidth-delay product (BDP). [10. (This value must be constrained by the receiver buffer size).

EMO can be used to determine the best suitable path for TCP connection and determine the optimal window size. There are two major advantages supported by EMO. First of all overheads of formula designing are eliminated. Without EMO we may need to integrate all the parameters (as per user requirements and type of network), where as EMO provides a platform to integrate these parameters as separate formulae.

Second major advantage is the Pareto set, which defines a non-dominant set of solutions, i.e., all Pareto solutions are equally good in performance. So, in case of congestion, link failure etc., computations required for computing alternative are reduced as equally good alternatives are already proposed.

This paper is divided into four sections. Section II introduces the basic concepts of Evolutionary Multiobjective Optimization. The proposed approach is discussed in section III. Result analysis is carried out in section IV. Section V is the conclusion and future scope.

II. EMO Basic Concepts

A multiobjective optimization problem (MOP) is defined as need of concurrent optimization of more than one objective. Mathematically we can define it as

Optimize

$F(Y) = \{f_1(Y), f_2(Y), f_3(Y)\ldots\ldots\ldots f_k(Y)\}$

Subject to

$C_1(Y) = 0$

$C_2(Y) >= 0$

Here, F(Y) represents the set of objectives to be optimized; k is the number of objectives in set F(Y) where Y is the set of independent variables. C_1 and C_2 represent the equal and non-equal constraints. These objectives may be conflicting in nature, i.e. improving one may result into deterioration of the other.

We look for 'trade-offs' as a single solution cannot simultaneously, optimize all the required objectives. Pareto-optimality is the term used. Say, we have a vector y^* such that,

$f_i(y) < = f_i(y^*)$ for all i= 1 to k

(not worse than, in terms of all objectives)

and

$f_j(y) < f_j(y^*)$ for at least one j

(is better than, in terms of at least one objective)

The solutions in vector y^* are called non dominant.

To solve MOP, evolutionary algorithms are used and hence the term Evolutionary Multiobjective Optimization (EMO). These algorithms are inspired from Evolution theory of Darwin stating survival of the fittest. They solve MOP; by treating solutions to any problem as population of individuals. Depending upon how good a solution is, a fitness value is assigned to each individual. This fitness value is derived from the functions/objectives which are optimized by the individual.

Similar to Darwin's biological evolution genetic operators, EAs involves following operators: Selection, Crossover and Mutation. Selection operator selects the individuals from parent population which will reproduce children solutions for the next generation. Crossover operator combines the two solution individuals resulting into two new solutions. For genetic diversity some changes are made into an individual, this is called mutation.

We need to put some bounds over the convergence of an evolutionary algorithm. For this we can use any stopping criteria such as limiting, number of generations, time limit, fitness limit etc. Thus, when EA stops we get a set of optimal solutions to our problem, which are equally good in terms of performance.

III. Proposed Approach

In this paper, two objective functions have been optimized, namely, end-to-end delay and BDP (bandwidth delay product). For efficient throughput, maximization of BDP [11] and minimization of end-to-end delay is done.

We have modeled the network as a graph G= (N, E), where N is the nodes and E edges. Among nodes we have source node S ϵ N and let D be some destination, D ϵ N. Let (i, j) ϵ E be a link from node i to node j. d_{ij} and b_{ij} be the delay and available bandwidth for the link (i,j). Say P represents the path from source to destination. Objective functions can be formulated as shown

$$\text{Delay} = \sum_{i,j\epsilon P} d_{ij} \qquad (1)$$

Delay for every link (i, j) from source to destination is added to calculate the total end-to-end delay for a given path.

$$BDP = \sum_{i,j\epsilon P} \min(b_{ij}) * 2 * d_{ij} \qquad (2)$$

The bottleneck bandwidth in the path P is multiplied with the round trip time. Assuming delay for a link is same for both way communications. This product must be constrained to maximum value of buffer size, in order to avoid buffer overflow at the receiver.

We limit our population size at each generation to be 50. Most common selection methods are roulette wheel selection and tournament method. We use tournament selection as it converges faster than roulette [12].

We have used two-point crossover as it mostly gives the best results [13].

To maintain the diversity, crowding distance parameter is used wherein, the individuals, with maximum crowding distance are selected. The Figure 1 below depicts the flow of our evolutionary algorithm.

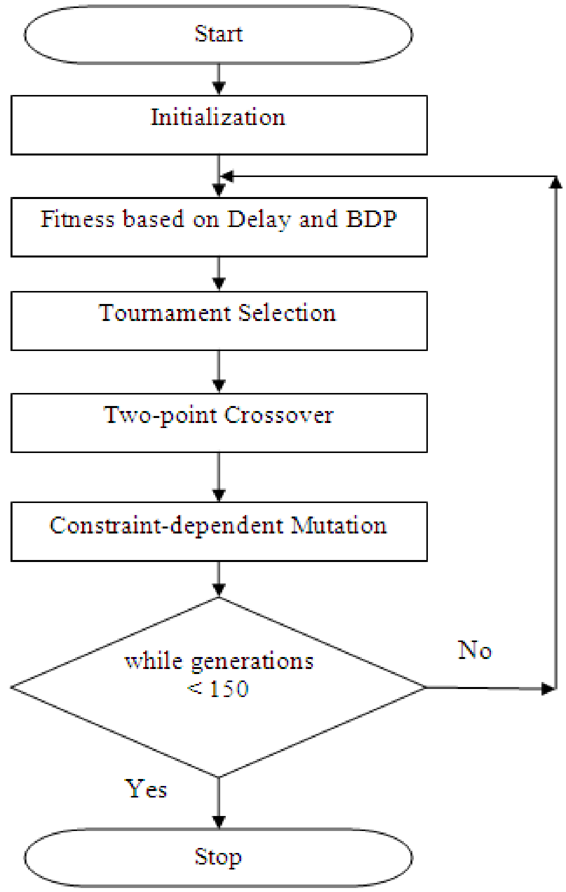

Figure 1 Evolutionary Algorithm Flowchart

IV. Experiment and Results

To evaluate the effect of EMO in increasing the throughput in TCP sliding window protocol we use gamultiobj solver available in MATLAB. We generate a fitness function using end-to-end delay and BDP parameters. The population size at each generation is limited to 50. Tournament method is used for selection where tournament size is 2. Two point crossover operator is utilized with 0.8 crossover fraction. An inbuilt function named distancecrowding is available in MATLAB which is utilized for diversity maintenance. For the selection of individuals from a Pareto front, 0.35 Pareto front population fraction is used. Constraint-dependent mutation is done Number of generation iterations is limited to 150. Figures 2, 3 and 4 below shows the pareto front values obtained at different generations. At end, we obtain the points where both the parameters are simultaneously optimized.

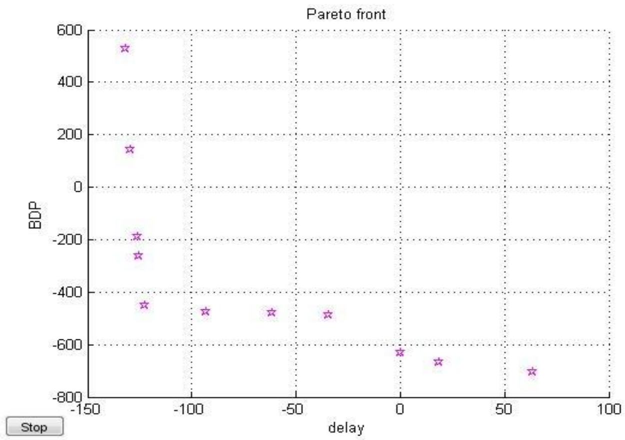

Figure 2 Pareto front at generation 37

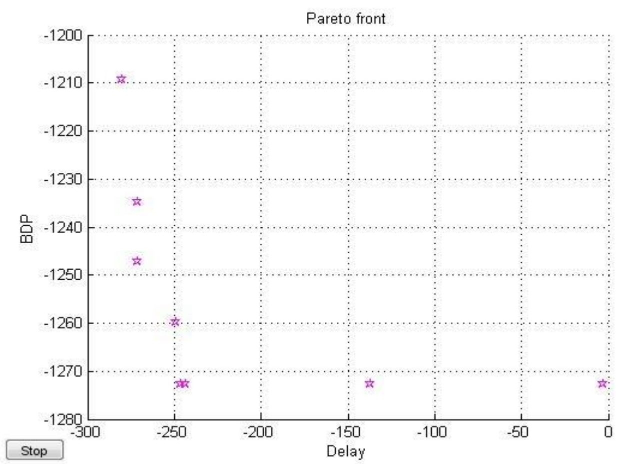

Figure 3 Pareto front at generation 99

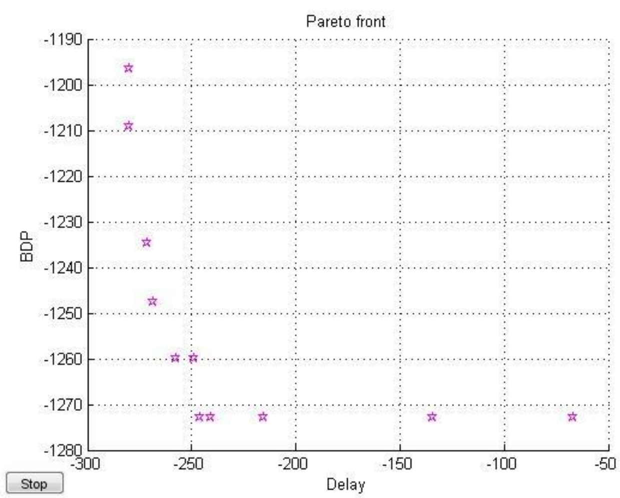

Figure 4 Pareto front at generation 114

V. CONCLUSION AND FUTURE SCOPE

EMO proves to be efficient method in calculating the best possible path for our TCP connection having minimum end-to-end delay and maximum bandwidth-delay product. The optimized value of BDP decides the optimum size for the window to have maximum throughput. Using EMO, the overheads of formula designing have been eliminated. We have separately mentioned the required parameters (equation 1 and 2). Also, at end of EA, we get a Pareto set of solutions. So, if a failure occurs for a selected link, then computations for determining the alternative path are reduced, as pareto-set defines the equally good possible alternatives.

Further improvements can be made by considering parameters like advertised window, buffer capacity etc to evaluate better window size.

Certain congestion avoidance or congestion control measures must be added on alongwith.

We have used the technique of EMO in TCP layer, which can also be implemented at almost all the OSI protocols to get optimized results.

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