Multiobjective Evolutionary Algorithms for Designing Capacitated Network Centric Communications

TRACK: Evolutionary Multiobjective Optimization

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1. PROBLEM DESCRIPTION

Contemporary network centric systems must provide an underlying structure for improved information communication, information awareness, sharing and collaboration between network elements. Such systems should enhance the quality of information awareness, security, improving sustainability, and mission effectiveness and efficiency. An element of network centric design is the solving of the communications or information flow problem. In this research, a multiobjective evolutionary algorithm (MOEA) is used to solve a variation of the multicommodity capacitated network design problem (MCNDP). This variation represents a hybrid communication network as found in network centric models with multiple objectives including costs, delays, robustness, vulnerability, and reliability. Nodes in such centric systems can have multiple and varying link capacities, rates and information (commodity) quantities to be delivered and received. Each commodity can have an independent prioritized bandwidth requirement as well. The nondominated sorting genetic algorithm (NSGA-II) MOEA is modified and extended to solve this generic MCNDP. Since the MCNDP is highly constrained, a novel initialization procedure and mutation method are also integrated into this MOEA. For this research, two objectives (total network cost and average number of hops) were optimized. Empirical results and analysis for 10-node and 20-node networks indicate that effective solutions can be generated efficiently.

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2. EXPERIMENTAL ANALYSIS

Experiments were decomposed into three categories - variable commodity flow, 100% commodity flow, and comparison with heuristics. Each category considers both a 10 node and 20 node case which are excellent benchmarks. The 10 node networks have 90 commodities that must flow over the data links to the nodes compared to 380 commodities for the 20 node networks. Each network was run for 50,000 MOEA evaluations. The M-NSGA-II is able to generate solutions that dominate the results of a quasi-Monte Carlo algorithm. The M-NSGA-II is able to generate better solutions because of mutation and selection because the search space is too large. The quasi-Monte Carlo algorithm cannot pass good building blocks to future generations, so it's search capabilities are limited by the vastness of the search space. These results lead us to attempt new experiments with the commodity flow set to 100%. This reduces the search space, but at the same time, may prevent feasible solutions from being realized. Here, the quasi-Monte Carlo method outperforms the M-NSGA-II with respect to average number of hops every time. The Pareto fronts generated by the two methods typically had about the same "spread" and roughly the same number of points. Results from an instance of the 20 node case with 100% flows indicate that the quasi-Monte Carlo method performed better with respect to the average number hops, but did worst in finding the total cost. Also, in the 20 node The quasi-Monte Carlo method typically generates much fewer Pareto front points and the "spread" of these points. The answer lies in the reduction of the search space and the fact that 100% flows always generate solutions with a smaller number of hops. The quasi-Monte Carlo algorithm creates 50,000 solutions from scratch, whereas the M-NSGA-II generates only 200 solutions and then mutates these over 250 generations. This smaller number of initial random solutions prevents the M-NSGA-II from adequately exploring the search space with respect to the average number of hops. A larger mutation rate can be imposed or a larger initial population size generated. While the average number of hops is decreased, the 100% flow method is unable to match the best total flow results of the variable method. Additionally, the Pareto front generated is less diverse compared to the variable method. The results showed that the flow rate plays a big role in the reducing the average number of hops, but has little effect, if any, on the total cost of the network. Because of the limited discussion of this critical real-world problem, the reader is directed to the authors' more innovative MOEA developments on this subject.

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