Comparison of Cooperative, Multiobjective Cooperative and Classical Evolutionary Algorithms for Global Supply Chain Optimisation

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ABSTRACT

This paper discusses global optimisation from a business perspective in the context of the supply chain operations. A two-silo supply chain was built for experimentation and three approaches were used for global optimisation: a classical evolutionary approach, a cooperative coevolutionary approach and a cooperative coevolutionary approach with non-dominated partner selection. The second approach produced higher quality solutions due to its use of communication between silos.

Categories and Subject Descriptors

I.2.m [**Artificial Intelligence**]: Miscellaneous

General Terms

Algorithms

Keywords

Evolutionary algorithms, cooperative coevolution, supply chain, global optimisation

1. INTRODUCTION

For the last few years most production-based businesses have been under enormous pressure to optimise their supply chains. Several studies have investigated optimisation techniques for various supply chain components.

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Large businesses typically breakdown their operations into components such as purchasing, production, and distribution. Each component operation can be referred to as a silo and for true global optimisation all silos must be taken into account. Optimisation of each individual silo in isolation may not lead to the global optimum. Thus, large businesses tend to be more interested in optimisation of their whole system rather than optimisation of single components of the system. This leads to the concept of *global optimisation from a business perspective*.

Research presented in this paper is an extension of research in [3]. In this paper a two component model is described, consisting of scheduling and vehicle routing problems. Sequential and cooperative coevolutionary approaches are taken to optimise this experimental supply chain. This paper extends [3] by describing an additional experiment that involves cooperative coevolution with non-dominated sorting based selection. Individuals for each of the silos apart from the combined cooperative fitness have also an individual fitness value, which can be treated as an objective. First non-dominated front of solution pairs based on two objectives is used to make a partner selection. Additional experiments with the same supply chain model can be found in [2] which include approach where solution for the second component is generated deterministically based on the solution from the first component. Also, experiments were conducted to determine the optimal parameter set for the cooperative coevolutionary experiment.

2. TWO-SILO SUPPLY CHAIN

A simulated supply chain with two silos has been built to investigate the issues connected with its global optimisation. The first silo is a production silo that assembles goods and then ships these finished products for consideration in to the second silo. It is represented in the literature as *job-shop scheduling problem* (JSSP). The second silo serves as a distribution component. It transports goods to customers using a fleet of trucks and it represents the *vehicle routing problem* (VRP). This simulates processes in real-world supply chains. Detailed description of the model can be found in [3].

3. ALGORITHMS

Two local algorithms to address JSSP and VRP are described in details in [3]. This paper compares three approaches to address this problem: classical sequential, cooperative coevolutionary and cooperative coevolutionary with non-dominated partner selection. The following subsection describes an algorithm based on non-dominated partner selection.

3.1 Cooperative coevolution with non-dominated partner selection

One of the main decisions one has to make when designing an evolutionary algorithm based on cooperative coevolution is choosing the method of selecting partner individuals. In this algorithm each silo in the supply chain can be treated as a separate problem without considering the other silos and, hence has its own objective. Production makespan is the individual objective for the first silo without considering the second one. For the VRP problem total length of the route is calculated as its objective. However, the objective of the second silo considers orders grouped in time buckets from the random individual of the first production silo (see [3]). This way each global solution (i.e. the combination of solutions from first and second silo) apart from the combined fitness have two additional independent fitnesses. Partner selection with the current approach works as follows. At each generation all current global solutions are put on the plane according to their two objectives. Then the first non-dominated set of solutions is found. A partner individual is randomly chosen from this set.

4. EXPERIMENTS AND RESULTS

A set of tests were developed based on the standard data sets for vehicle routing and job-shop scheduling problems. JSSP data sets were taken from instances proposed by Taillard in [4] in particular ta11, ta35, ta51, ta70 and ta71 were used. For VRP test cases instances proposed by Christofides et al. [1] were taken, in particular CMT-1, CMT-2 and CMT-3. In table 1 column *Size* corresponds to the number of customers and hence the number of orders in the experiment. The following combinations of datasets were used: ta11 with CMT-1, ta35 with CMT-1, ta51 with CMT-2, ta70 with CMT-2 and ta71 with CMT-3. The missing link between two silos is the mapping between job orders and customers was developed for each data set.

Due to stochastic nature of evolutionary algorithms, each experiment was executed 50 times so as to allow for statistically accurate results. Results average, standard deviation, minimal and maximum of all runs were recorded.

Parameters for the classical sequential and cooperative coevolutionary algorithms can be found in [3]. These parameters were chosen by the series of manual exploratory experiments. Table 1 shows the comparison of the results. Here *Seq* corresponds to the sequential approach, *Coev* - to the first coevolutionary approach and *CND* - coevolutionary approach with non-dominated partner selection. In all the data sets we can see that both coevolutionary approaches produce better results on average with smaller standard deviation. Despite our hopes towards non-dominated parent selection algorithm, it did not produce better results than simple random selection. Number of fitness evaluations in coevolutionary approach is about 1.4 times larger than in the classical one. However, increasing number of fitness evaluations in the latter method would not produce significantly better results as after number of generations used in the current algorithm it converges to the local optimum. Another issue with cooperative approach is that fitness evaluation of each pair of individuals is computationally expensive simulation. With classical approach simulation needs to be run only for evaluation of VRP individuals.

Table 1: Run results

Exp	Size	Avg	Min	Max	StdDev
Seq	20	2603.28	2407.01	2800.69	93.57
Coev	20	**2505.59**	2365.35	2722.77	69.18
CND	20	2527.40	2375.39	2702.21	78.69
Seq	30	3761.86	3451.21	4127.81	105.98
Coev	30	**3514.18**	3389.71	3597.83	68.16
CND	30	3569.85	3336.29	3798.74	115.41
Seq	50	5941.21	5453.55	6390.89	205.68
Coev	50	**5652.39**	5372.54	5969.93	133.99
CND	50	5840.32	5463.54	6215.18	142.15
Seq	50	6387.10	6046.69	6729.65	156.76
Coev	50	**6095.35**	5732.16	6336.52	149.86
CND	50	6287.59	5997.84	6575.29	141.08
Seq	100	11859.45	11205.47	12532.39	295.91
Coev	100	**10762.09**	10312.97	10976.93	171.37
CND	100	11265.19	10733.88	11791.87	245.41

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6. REFERENCES

[1] N. Christofides, A. Mingozzi, and P. Toth. The vehicle routing problem. *Combinatorial Optimization*, page 431Ű448, 1979.

[2] M. Ibrahimov, A. Mohais, S. Schellenberg, and Z. Michalewicz. Comparison of different evolutionary algorithms for global supply chain optimisation and parameter analysis. In *2011 IEEE Congress on Evolutionary Computation*, 2011.

[3] M. Ibrahimov, N. Wagner, A. Mohais, S. Schellenberg, and Z. Michalewicz. Comparison of cooperative and classical evolutionary algorithms for global supply chain optimisation. In *IEEE World Congress on Computational Intelligence*, 2010.

[4] E. Taillard. Benchmarks for basic scheduling problems. *European Journal of Operational Research*, 64(2):278–285, January 1993.