Algorithm Selection for Population-Based Optimization of Networked Structures

Adam Dziomdziora[1][0000-0002-9667-8689]
and Przemysław Ignaciuk[1][0000-0003-4420-9941]

Lodz University of Technology, Institute of Information Technology
Wolczanska 215, 90-924 Lodz, Poland
adam.dziomdziora@dokt.p.lodz.pl

Abstract. This paper addresses the problem of optimizing goods flow in complex logistic networks influenced by significant demand uncertainty. For that purpose, two population-based algorithms – Biogeography-Based Optimization (BBO) and Particle Swarm Optimization (PSO) – are compared. As considerable computational resources are needed to determine the cost function value, one opts for an algorithm that reaches convergence in the fewest possible steps. The considered fitness function balances the bullwhip effect and transportation cost reduction. For topologies up to 14 nodes, PSO happens to decrease the cost function more than BBO. However, it requires more iterations to reach the optimum. When the interconnection complexity grows, PSO demands larger population size, thus more computations to outperform BBO. For larger topologies, BBO proves more efficient.

Keywords: Population-Based Algorithms · Bullwhip Effect · Logistic Networks · Time-Delay Systems.

1 Introduction

One of the economic areas with rising profitability is logistics, which incorporates manufacturing, transport, and trade [1, 2]. Despite substantial effort to limit its impact, the bullwhip effect (BE) may thwart the process of goods distribution. The BE manifests itself as an intensified variability of demand projected onto resource replenishment decisions. It leads to unnecessary shipments, prolonged delays, and stock accumulation at subsidiary nodes [3], thus should be avoided as early as in the network planning phase. Owing to the significant computational complexity in solving the optimization task, population-based algorithms are considered as a viable alternative to the traditional methods [4]. However, since the cost function calculation in the considered class of problems is demanding, only those methods that permit reaching the optimum in a small number of steps (iterations) are suitable. The purpose of this work is to examine two population-based algorithms: Biogeography-Based Optimization (BBO) and Particle Swarm Optimization (PSO) in optimizing the operational efficiency and preventing the BE in the systems managed by the classical order-up-to inventory policy [5]. The optimization objective is to shape the interconnection structure, i.e., to decide how intensively a given transportation link (channel) should be used to avoid the BE.

2 Population-Based Optimization

The decisive factor behind cost-efficient operation of a logistic network is an appropriate choice of channel utilization coefficients. The optimization procedure yields a matrix of coefficients reflecting the network structure with reduced propensity for BE formation and smaller transportation costs. Here, BBO and PSO are evaluated as a computational platform for solving the optimization task. BBO has emerged recently as an attractive method for solving complex optimization problems [6], whereas PSO is a mature and well-explored method in diverse applications [7].

2.1 Biogeography-Based Optimization

BBO is an evolutionary, population-based algorithm that derives from the observation of species movement among separate areas called islands. Its power lies in merging examination with exploitation originating from migration. BBO does not require computing fitness function derivatives, yielding an attractive computational platform. The elitism mechanism, missing in PSO, seems to have a crucial impact on the algorithm performance toward cost function reduction.

2.2 Particle Swarm Optimization

PSO is an optimization procedure originating from swarm intelligence with random movement of candidate solutions. It delivers a population-based search procedure where the set of feasible solutions evolves to yield an optimum. Each particle denotes a viable solution to the problem. PSO starts with a swarm - population - that moves through the search space to find the optimal solution. PSO is distinctly different from BBO as it does not utilize crossover and mutation stages. It models the dynamics of candidate solutions through the search space, where each particle moves with a predefined velocity. The experience of every particle and its neighbors governs the swarm movement. Moreover, the swarm communicates to yield attuned parameters for all particles. In an epoch, each particle holds its local best fitness. Also, the global best of the swarm is updated accordingly. The main idea of PSO is to accelerate particles toward their local best and the global best in each iteration.

3 System Model

The examined class of system concentrates on the interaction between two types of actors: external sources – supplying goods to the controlled network and controlled nodes – generating replenishment signals and serving as intermediate sources for other controlled nodes. The system encompasses N controlled nodes and M external sources, connected by unidirectional links. The system used in experiments is implemented with the methodology introduced in [4]. Here, the simulation size Θ is calculated from the generation size g=10^2, simulation horizon H=10^3 and population size p as:

$$\Theta = g * H * p. \tag{1}$$

4 Numerical Study

In the experiments, the bullwhip effect is quantified through a network indicator (BI) ω, transportation costs Ψ and fitness function FF=Ψ*Ω as in [9]. System results from conducted optimization are grouped in Table 1, where the highlighted ones denote the best minimization. Example topology (Network A) is illustrated in Fig. 1. According to a set of recommended PSO parameters, for the optimal algorithm operation, the population size requires large values, e.g., for a 20-dimension problem, Pendersen recommends p=60. Hence, 20-dimension and greater networks (A and B), resulted in lower costs with BBO. Smaller ones (C and D) achieved better cost reduction with PSO, having p=16 for 11-dimension Network D and p=32 for 14-dimension topology Network C. Also, one should notice that enlarging the population size significantly prolongs the overall simulation time. On the other hand, PSO could obtain better results with appropriately adjusted population size, though it requires further investigation.

Table 1: Population size dependence for networks with p=16 $\vee$ 32.

(a) Transportation costs

***p*=32**	Nodes	Ψ (€)	Ψ_{PSO}	Ψ_{BBO}
A	N=25, M=6	1.39 x 10^8	1.27 x 10^7	**9.14 x 10^6**
B	N=15, M=5	1.45 x 10^7	3.7 x 10^6	**3.01 x 10^6**
C	N=12, M=2	8.77 x 10^7	**2.27 x 10^6**	2.87 x 10^6
D	N=9, M=2	1.94 x 10^7	**1.22 x 10^6**	1.56 x 10^6
***p*=16**	Nodes	Ψ (€)	Ψ_{PSO}	Ψ_{BBO}
A	N=25, M=6	1.46 x 10^8	1.43 x 10^7	**9.31 x 10^6**
B	N=15, M=5	1.45 x 10^7	3.7 x 10^6	**3.01 x 10^6**
C	N=12, M=2	5.86 x 10^7	3.76 x 10^6	**3.38 x 10^6**
D	N=9, M=2	1.88 x 10^7	**1.73 x 10^6**	1.8 x 10^6

(b) BI

	Ω	Ω_{PSO}	Ω_{BBO}
A	14.99	4.74	**4.22**
B	7.36	3.7	**3.17**
C	18.07	**3.08**	3.17
D	8.21	3.12	**2.99**
	Ω	Ω_{PSO}	Ω_{BBO}
A	16.31	4.94	**4.29**
B	4.89	3.42	**3.2**
C	12.4	3.71	**3.16**
D	7.27	2.81	**2.68**

5 Conclusions

In 14-node and smaller networks, PSO yields more profound cost reduction than BBO. However, it performs better only after the population size is increased

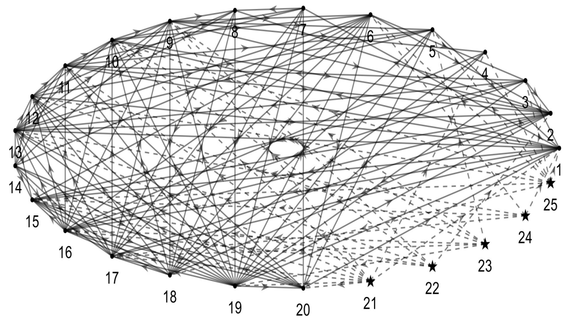

Fig. 1: Example network structure. Stars denote the exterior suppliers (M=5), and circles illustrate controlled nodes (N=20).

from 16 to 32 individuals, thus significantly extending the simulation time. In 15-node and bigger topologies, BBO outperforms PSO and converges faster. In the future studies, BBO will be compared with PSO in the network optimization under a much larger population size setting, e.g., $p>100$.

Acknowledgment

This work has been performed in the framework of a project "Robust control solutions for multi-channel networked flows" no. 2021/41/B/ST7/00108 financed by the National Science Centre, Poland. This work has been completed while the first author was the Doctoral Candidate in the Interdisciplinary Doctoral School.

References

1. Sumukadas, N.: Are you ready for your next product recall crisis? Lessons from operations and supply chain management. Bus. Horiz. **64**(2), 211–221 (2021).
2. Speranza, M.: Trends in transportation and logistics. Eur. J. Oper. Res. **264**(3), 830–836 (2018).
3. Lee, H., Padmanabhan V., and Whang S.: The Bullwhip Effect in Supply Chains. Sloan Manage. Rev. **38**(3) (1997), 93–102 (1997).
4. Ignaciuk, P. and Wieczorek, L.: Continuous Genetic Algorithms in the Optimization of Logistic Networks: Applicability Assessment and Tuning. Appl. Sci. **10**(21), 7851 (2020).
5. Axsäter, S.: Inventory control. Springer International Publishing (2015).
6. Simon, D.: Biogeography-based optimization. IEEE Trans. Evol. Comput. **12**(6), 702–713 (2008).
7. Pedersen, M.: Good parameters for particle swarm optimization. Technical report, Hvass Laboratories, www.hvass-labs.org (2010).
8. Simon, D.: Evolutionary optimization algorithms. John Wiley & Sons (2013).
9. Ignaciuk, P. and Dziomdziora, A.: Quantifying the Bullwhip Effect in Networked Structures with Non-trivial Topologies. In: ACM International Conference Proceeding Series, ACM, New York, USA, 62–66 (2020).