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BBO in solving complex optimization problems – bullwhip effect reduction in logistics networks

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Abstract. *This chapter addresses Biogeography-Based Optimization (BBO) implementation for counteracting the bullwhip effect in logistic systems influenced by uncertain demand. The considered class of systems comprises two types of actors – controlled nodes and external sources – connected by unidirectional links. In this paper, the application of BBO is proposed to support the optimization problem of proper channel allocation in transportation links. BBO allows one to perform simulation-based optimization and provide desirable operating conditions to answer a priori unknown, time-varying demand. The effectiveness of the goods distribution process governed under a base-stock policy includes the objective function of mitigating the bullwhip effect and minimizing transportation costs. The introduced optimization problem is solved using BBO to find an optimal channel allocation matrix for a given topology. The results are verified in extensive simulations of a real-world logistic network.*
Keywords: *Biogeography-Based Optimization, Bullwhip Effect, Logistic Networks, Time-Delay Systems*

1. Introduction

In modern times, despite the pandemic situation, one can notice a notable development of the global industry. Despite the COVID-19 worldwide financial crisis, numerous new industrial branches have appeared, e.g., cryptocurrency industry. Moreover, many existing ones have made significant progress [1, 2]. One of the economic sectors with increasing profitability is logistics, which incorporates production, transport, and trade activities during the distribution processes in complex (multi-input multi-output entity) logistic networks [3]. However, a severe systemic distortion influences resource management in transportation networks -

the bullwhip effect (BE). The BE manifests itself as an enhanced variability of demand transmitted into the goods ordering signal. An example distribution system is illustrated in Fig. 1. In addition to lowered earnings, the BE leads to unnecessary shipments, prolonged delays, and resource accumulation at subsidiary nodes [4]. Due to the high interconnection complexity in real-world distribution systems, the optimization of goods transportation in logistic networks is a computationally demanding task. One of the fastest-growing in popularity algorithms, from various nature-based methods used to tackle computationally-intensive optimization problems, is Biogeography-Based Optimization (BBO). The purpose of this paper is to evaluate the usefulness of BBO in logistic network performance by counteracting the bullwhip effect when subjected to the control of the popular order-up-to (OUT) [5] – inventory policy.

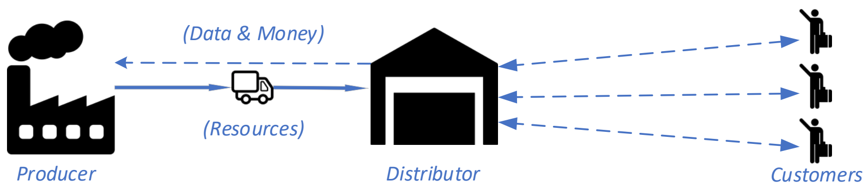

Figure 1: An example supply chain.

Many scientists proposed methods to reduce the harmful impact of the BE on logistic system performance [6–9]. They emphasised statistical analysis and operations research techniques. A different promising idea was to implement robust control techniques [10–13]. Nevertheless, in real-world systems, conventional methods are still preferred, e.g., OUT policy. The BE triggers in the systems organized in serial and arborescent topologies governed by the OUT policy have been given in [14]. Introductory treatment of more complex networked topologies has been examined in [15]. A modified OUT policy, introduced for centralized structure management, was optimally tuned for holding and lost-sales diminution [16]. In real-world transportation networks, the optimization typically targets delays and holding, or transportation costs decrease. Determining the optimal solution for those objectives, analytically or numerically (e.g., through full search), is computationally demanding. Hence, non-weighted procedures, e.g., alternating, hierarchical, or phased optimization techniques [17, 18], are used. For instance, to reduce both the total cost of travelers and the number of required transfers in transportation systems, Arbex and da Cunha [17] introduced the Alternating Objective Genetic Algorithm. In extension to the traditional one [19, 20], it enabled them to apply local search techniques to handle the infeasibility of newly created individuals. Additionally, enhanced Simulated Annealing has recently been considered in transportation network optimization [18]. Nevertheless, the implemented objectives neglect a primary problem that hinders current systems: to operate efficiently in time-varying, perturbed conditions. Therefore, in this work, the OUT policy optimization explicitly targets the diminution of a systemic distortion – the BE with the BBO implementation. The considered class incorporates systems with a complex networked topology, with goods reflow subject to non-negligible time delay. The OUT inventory policy manages the ordering workflow by governing lot sizing. The objective is to design the network layout, i.e., to determine how intensively a given transportation path (channel) of goods distribution should alleviate the BE. Consequently, a matrix of coefficients yielding diminished BE and transportation costs within a given time horizon is established. The logistic system could also interpret the coefficients in terms of order splitting, i.e., which part of the order established by a controlled node is planned for retrieval from a particular supplier (a neighboring controlled node or an external source). The optimization task is solved with modern population-based evolutionary techniques – BBO. The obtained tuning method for the coefficients modification is straightforward in implementation and do not demand extensive computational power. As explained in the conducted research, the commonly practiced oversight of the planning phase by uniform lot partitioning between the transportation channels is inaccurate since it leads to augmented disturbance and considerable expenses. The proposed intelligent planning technique allows one to place the logistic industry representative in a desirable situation with respect to the competition, diminishes transportation costs, and avoid the BE.

2. Related works

Biogeography is the study of the geographical distribution of biological organisms. Simon used the mathematics of biogeography as the grounds for the BBO implementation in [21], with its dynamic model extension presented in [22]. Afterward, Yang et al. in [23] proposed a logistic system design model based on the hybrid BBO algorithm, which incorporated the cost risk and shared service level. However, they do not examine the impact of implemented adjustments on the BE formation. Zhang et al. in [24], in turn, combined the BBO algorithm with the intuitionistic fuzzy entropy weight approach to optimize the manufacturing inside the supply chain. Still, they omit the current industry requirements, such as energy consumption or customer satisfaction.

Besides BBO, other population-based approaches were implemented in the logistic sector optimization. Nia et al. in [25] adopted Ant Colony Optimization for total cost minimization in goods distribution systems. However, they neglected the validation of their results on the supply systems with intricate network topology. Besides, Xin et al. in [26] introduced an Improved Discrete Whale Swarm Algorithm including differential evolution, enhanced search, and job-swapped mutations to reduce both makespan and energy consumption during varying transportation time. Still, they omit in the investigation uncertain customer demand having node malfunctions (examined by Ignaciuk and Dziomdziora in [27]). Then, Kamhuber et al. in [28] proposed a procedure for multi-objective optimization inside a production planning system by using the Genetic Algorithm to metaheuristic optimization. Contrary to their study, this work implicitly targets transportation cost minimization and goods distribution distortion reduction with the population-based heuristic procedure, including uncertain lead times and varying customer demand. [15], in turn, used the Continuous Genetic Algorithm to diminish holding costs, including operational costs and customer satisfaction. However, they did not consider networks with unpredictable time-varying parameters and configurations, e.g., installations with incorrect inventory records. In this work, the BBO algorithm with mutations is implemented to solve complex optimization problems by counteracting the bullwhip effect in the logistics network. Using the provided method, one can improve the transportation channel utilization coefficients to alleviate the BE systemic distortion structurally. Using the proposed intelligent planning technique in the distribution systems, one may decrease the transportation costs, concurrently maintaining high customer satisfaction.

3. System model

3.1. Interconnection structure

The considered class of system handles interaction among two types of actors:

- external sources – responsible for supplying the goods to the controlled network, but are not influenced directly by the imposed demand
- controlled nodes – responsible for assisting both as intermediate sources for other controlled nodes and generating replenishment signals for the external sources to satisfy the customer demand.

The system incorporates N-controlled nodes and M-external sources, connected by unidirectional links. The links are characterized by:

- lot partitioning coefficient – to be adjusted in the optimization task – that dictates how intensively a provided channel (transportation link) will be utilized,

- lead-time delay – the delay in order satisfaction (the transport delay),
- transportation cost – associated with the distance between the nodes. Networks with detached nodes, i.e., without connection to any supplier; or self-suppling nodes, are not considered.

3.2. Node dynamics

Let $t = 0, 1, 2, \ldots, H$ denote the duration of time, where H denotes the time horizon. The stock level at node i accumulates according to

$$x_i(t+1) = x_i(t) + \underbrace{\sum_{j=1}^{N+M} \delta_{ji} u_i(t-\beta_{ji})}_{\text{incoming shipments}} - \underbrace{\sum_{j=1}^{N} \delta_{ij} u_i(t)}_{\text{outgoing shipments}} - \underbrace{d_i(t)}_{\text{customer demand}} \tag{1}$$

where:

- δ_{ji} – the lot partitioning coefficient for the orders placed by node i at node j,
- β_{ji} – the lead-time delay of goods relocated from node j to i,
- $u_i(t)$ – the quantity of goods demanded by node i in period t from its suppliers, including external sources and intermediate nodes,
- $d_i(t)$ – the customer demand placed at node i in period t. It exhibits random variations within $[0, d_i^{max}]$, where d_i^{max} denotes an estimate of the maximum.

The channel allocation matrix groups lot partitioning coefficients:

$$\Delta = \begin{bmatrix} 0 & \delta_{12} & \cdots & \delta_{1N} \\ \delta_{21} & 0 & \cdots & \delta_{2N} \\ \vdots & \vdots & \ddots & \vdots \\ \delta_{N1} & \delta_{N2} & \cdots & 0 \\ \vdots & \vdots & \cdots & \vdots \\ \delta_{N+M,1} & \delta_{N+M,2} & \cdots & \delta_{N+M,N} \end{bmatrix}_{N+M \times N}, \tag{2}$$

$\delta_{ji} \neq 0 \Rightarrow \delta_{ji} = 0$ and for any i, j:

$$0 \leq \delta_{ji} \leq 1 \text{ and } \sum_{j=1}^{N+M} \delta_{ji} = 1. \tag{3}$$

where each column of the matrix Δ has to sum to the value of 1, meaning that from a given node, all the resources are appropriately split among other controlled nodes. Also, any node can not obtain more than 100% of the available lot. Consequently, the negative values are forbidden, as each part of the resources to be shipped must be non-negative.

3.3. OUT inventory policy

To control the goods reflow in the network, one may use the OUT inventory policy. Here it is implemented in a distributed mode, i.e., individually at the controlled nodes. Controlled node i generates the stock replenishment signal according to

$$u_i(t) = x_i^{ref} - x(t) - \Gamma_i(t), \tag{4}$$

where x_i^{ref} denotes the reference level – to be assigned to maximize sales [29], and $\Gamma(t)$ denotes the open-order volume, i.e., the goods in transit not yet arrived at the ordering node due to lead-time delay.

3.4. Bullwhip effect in logistic networks

From the logistic perspective, one should consider more involving topologies than a serial chain to evaluate the system propensity to the BE formation. An example networked structure is depicted in Fig. 2, where $n_{1–3}$ indicates controlled nodes, $m_{1,2}$ denotes external sources, $\delta_{ji}u_i(t)$ – represent internal demand imposed on node n_1 and n_2 from n_3, respectively, and $d_{1–3}$ is the exogenous demand imposed on the nodes. In serial connections, one of the most popular measures used

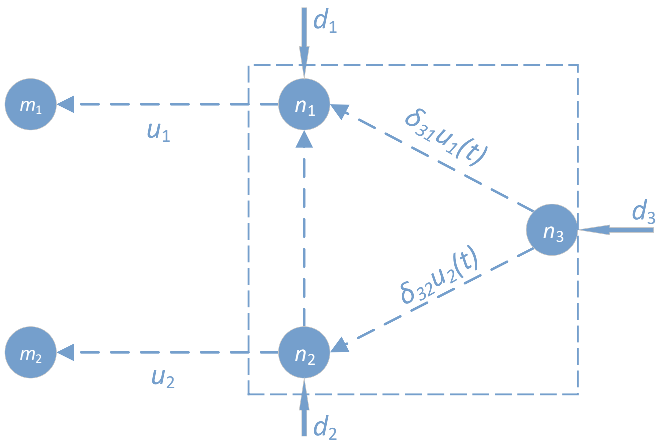

Figure 2: A five-node network.

to quantify the BE is order-to-variance ratio [30]. There is a limited possibility of designating the lateral nodes in networked configurations and using them to establish a bullwhip indicator (BI) in a transportation system, as it commonly happens in serial chains. The lack of reasonable measurement methods, allowing for the BE quantification in networked configurations, motivates the search for alternatives [31]. The proposed BI should provide the BE quantification technique, judging the networked topology as a holistic, multi-input multi-output entity. Therefore, for the BE quantification in networked structures, a vector-based measure will be defined. Alternatively to concentrating on one node, aggregated demand and external replenishment signals will be evaluated. In the time horizon of H periods, the record of replenishment signal imposed on node i at an external supplier $u_i^H = [u_i(0)\ u_i(1)\ \ldots\ u_i(H{-}1)]^T$. Likewise with respect to the demand imposed on node i one has $d_j^H = [d_j(0)\ d_j(1)\ \ldots\ d_j(H{-}1)]^T$. The demand may be placed at any node. Similarly, any node may generate a replenishment signal for any external supplier. The introduced BI, based on the Euclidean distance, is determined as:

$$\omega = \frac{\sqrt{\sum_{i\in\Omega_e} (\mathrm{var}[u_i^H])^2}}{\sqrt{\sum_{j\in\Omega_d} (\mathrm{var}[d_j^H])^2}}. \tag{5}$$

where Ω_e denotes the set of node indices on which replenishment signals is generated for the external suppliers, and Ω_d implies the set of node indices where the demand is imposed. For the external actors, the controlled network is treated as a black-box entity. $\omega > 1$ indicates that the BE has appeared. The larger the value of ω, the more serious the BE.

3.5. Transportation costs

One may calculate the transportation costs by counting the distance of the transportation tracks and the quantity of shipped goods. In the time horizon of H periods, transportation cost equals

$$\Psi = \sum_{k=0}^{H-1} \sum_{i=1}^{N} \sum_{j=1}^{N+M} \delta_{ji} u_i(t) \varphi_{ij} \phi \tag{6}$$

where φ_{ij} denotes the transportation cost on the route i-j, calculated as a product of a fixed unitary price ϕ and the distance connecting the nodes.

3.6. Customer satisfaction

A properly operating logistic system is expected to secure a high level of demand satisfaction. The customer satisfaction rate at node i is calculated as

$$\xi_i = \frac{\sum\limits_{t=0}^{H-1} h_i(t)}{\sum\limits_{t=0}^{H-1} d_i(t)}, \tag{7}$$

where $h_i(t)$ is the satisfied demand at node i in period t. Hence, a mean satisfaction level in the system can be estimated as

$$\vartheta = \frac{\sum_{i=1}^{N} \xi_i}{N}. \tag{8}$$

4. Biogeography-based optimization

The crucial factor behind the cost-efficient OUT policy performance is proper selection of lot partitioning coefficients. In modern logistic systems, it should be done simultaneously for all the controlled nodes, which is computation demanding due to complex networked topology. BBO enables the self-regulation of this process by numerical evolution of channel coefficients. BBO is a population-based method that originates from inspecting a species evolution among separated zones called islands. In addition to numerous advantages, e.g., integrity, flexibility, efficiency, and high performance, BBO does not require objective function derivatives. One may recognize BBO as a suitable heuristic search technique in complex optimization problems, as it incorporates both the examination and exploitation originating from migration [21]. The BBO algorithm is illustrated in Fig. 3. Its steps are described in the following sections.

4.1. Initialization

The initial two steps of the flowchart shown in Fig. 3 constitute the initialization stage of the optimization process. First, the channels are uniformly allocated among the nodes. In the initial simulation sequence, it is assumed that at each node, a random demand signal is imposed during the entire simulation period equal to the Poisson distribution of the maximum value assumed for this node. The initial transportation cost Ψ_{max} and ω_{max} are determined subsequently and set as the maximum limit value for further computations. Although the initial channel allocation assures full customer satisfaction, the transportation cost is very high with the significant BE – goods are transported excessively under a non-optimal path. Further stages of the optimization process aim to reduce both the BE and transportation costs, while maintaining a high customer satisfaction rate.

4.2. Population size

To adjust the BBO method for efficient convergence during the optimization, one needs to set the population size correctly. Hence, inside each epoch of the

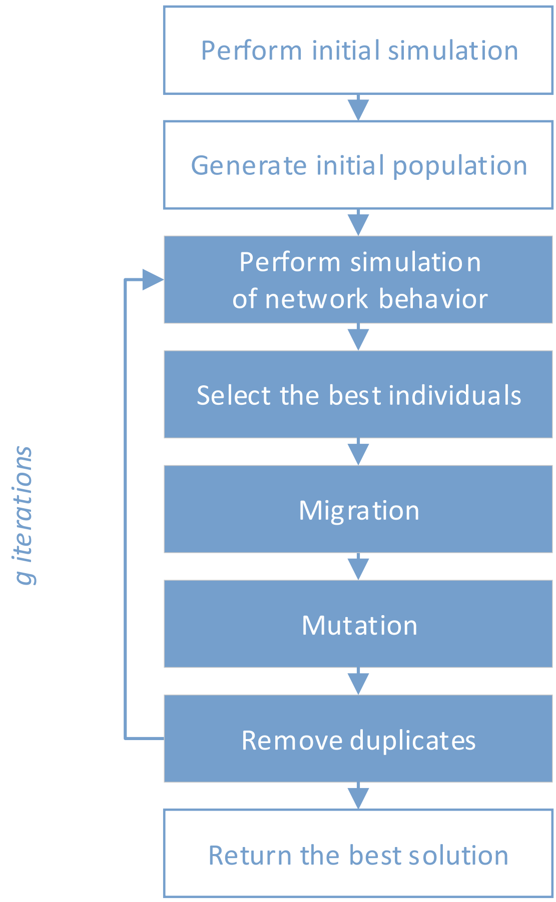

Figure 3: BBO algorithm flowchart

BBO operation, population size is determined as

$$\eta = \frac{3 * (N + M)}{\zeta}, \tag{9}$$

where ζ is the the number of links per node. The network complexity ζ is inversely proportional to the population size η. The dependence results from the examination of various network parameters, as presented in Table. 1 (defined in Section 5).

4.3. Fitness function

A suitable fitness function is fundamental for BBO proper operation and its effectiveness in solving complex optimization problems. This function defines dependencies connecting the particular system elements and their significance for the ensuing solution. It permits one to link a precise solution to the required optimum and impact successive population creation. A properly defined fitness function should be normalized and effective in computation. In the considered class of logistic systems, three factors have a determining impact on the solution:

- $\varPsi$ - transportation costs, $\varPsi \in [0, \varPsi_{max}]$,
- ω - the introduced BI for networked systems, $\omega \in [0, \omega_{max}]$,
- ϑ - mean customer satisfaction rate, $\vartheta \in [0, 1]$.

The goal of the considered optimization process is to determine a channel allocation matrix Δ so that the logistic system can fulfill the external demand with low transportation costs yet mitigating the BE. For this purpose, the following fitness function has been used:

$$\min\,(\delta_{ij}) J = \mathbf{\Psi}(t)\omega\vartheta^{-1}. \tag{10}$$

s.t. (1) – the stock level dynamics, (3) – the channel allocation restriction, and (4) – the method of replenishment signal calculation. The fitness function allows one to gauge how well adjusted is a candidate solution and evaluates it with respect to others.

4.4. Selection

All candidate solutions generated within the optimization problem are called individuals. In the considered class of systems, these are represented by a unique instance of transportation channel utilization matrix Δ. One may assume that the population size equals η, z_k denotes the k-th individual of the population, and the considered optimization problem dimension equals p. Moreover, $z_k(s)$ denotes the s-th independent variable in z_k, where $k \in [1,\eta]$ and $s \in [1,p]$. During every generation, for all solution features in the k-th individual, probability that s-th independent variable is selected for replacement in z_k equals ι_k (the immigration rate), for $k \in [1,\eta]$ and $s \in [1,p]$. If a solution feature is selected for a replacement, the emigrating individual having a probability equivalent to the emigration probabilities ε_i (the emigration rate) is selected. One may utilize any fitness-based selection method for the selection phase. If the popular roulette-wheel approach is adopted, then the probability that z_k is selected for emigration equals

$$\Pr(z_k) = \frac{\varepsilon_k}{\sum_{i=1}^{\eta} \varepsilon_i} \tag{11}$$

4.5. Migration

In the migration stage, an island – a set of individuals – matches the set of a predefined size containing Δ matrices, and a separate population comprises a set of islands. Poorly adjusted individuals are expected to receive new features from good individuals, quite like less habitable islands are expected to get multiple immigrants from highly habitable islands. The process of incorporating new features into poor individuals can increase the quality of those individuals. The highest possible immigration rate to the habitat is I, which happens when the island is without species, marked above the immigration curve. With the increase of species inside, the island becomes more crowded. Hence, fewer species can successfully survive immigration, and the immigration rate drops. The most significant achievable number of species for the habitat to hold is S_{max}, at which the immigration rate equals zero. Consequently, one may consider the emigration curve. If the island is without any species, then the emigration rate equals zero. While the number of species on the island rises, it becomes extra crowded. Therefore, more species could leave the island, and the emigration rate rises. The maximum emigration rate equals E, while the island holds the most significant number of species that it may support. One may assume that an equal species number curve describes every BBO individual with $E = I$ for integrity. Fig. 4 represents the migration rates in a BBO algorithm with the specified assumptions. S_1 denotes a low-quality individual, while S_2 signifies a good individual. The immigration rate for S_1 will be proportionately high, meaning that it is about to acquire new features from different candidate solutions. The emigration rate for S_2 will be relatively high, which indicates that it will be expected to share its features among surrounding individuals. ι is the immigration rate for a individual and ε is its emigration rate. One may call the illustrated graph a linear migration model because the ι and ε values follow the linear functions of fitness.

4.6. Mutation

The last step of the BBO algorithm is mutation. The mutation rate is one of the primary parameters of BBO. The initially selected coefficient influences the mutation, which infrequently occurs in the described implementation. Mutation indicates replacing a randomly chosen element of an individual with a random value from the analyzed domain. The element of an individual matches a single channel utilization coefficient – δ_{ij} – within the allocation matrix. A randomly selected channel utilization coefficient can be substituted with a newly generated one if a solution is qualified to mutate. The mutation rate is the probability that an element of an individual will mutate after a mutation operation. The matrix of channel utilization coefficients is created by randomly mutating the matrix columns before

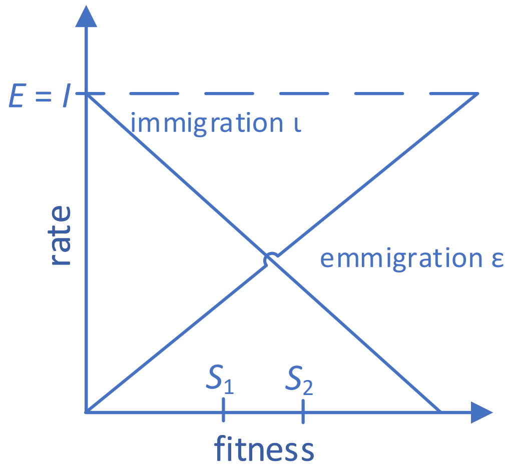

Figure 4: BBO feature-sharing relationship.

continuing with a subsequent iteration. It is achieved by randomly increasing or decreasing each matrix entity value – δ_{ij}. The value of the last column element is determined as $1 - \sum_{i=1}^{N+M-1} \delta_{ji}$.

5. Numerical study

The system analyzed in the numerical study represents the European logistic network of a company from the premium-clothes fashion industry. The firm central warehouses are in Paris and Milan. The business network spreads over Central Europe, with the distribution hubs in Brussels, Munich, Berlin, Warsaw, Cracow, Graz, Prague, and Budapest, as shown in Fig. 5. The network graph representation is presented in Fig. 6. The quantities displayed over the arrows denote the lead times and transportation costs associated with the links.

The goal is to determine the optimal lot partitioning coefficients for controlled nodes to reduce the BE and transportation costs. Initially, the lot partitioning is divided equally among the routes, as is conventional in the literature. The simulation horizon equals $H = 10^3$ periods. The demand, placed at any controlled node, manifests stochastic fluctuations created according to the Poisson distribution with $\mu = 0.6$. The unitary transportation price is $\phi = 0.04$ € per 10 km. Network A comprise 10 nodes ($N = 8$, $M = 2$), with the number of links per node ($\xi = 2.87$), and a search space of 6.54 x 10^{28} possible solutions, which is impossible for full search. Consequently, the BBO heuristic search is applied. Each population in BBO contains 10 individuals, according to (9). The generation number is limited to $g = 100$ epochs. Mutations are not included during the emigration rates update.

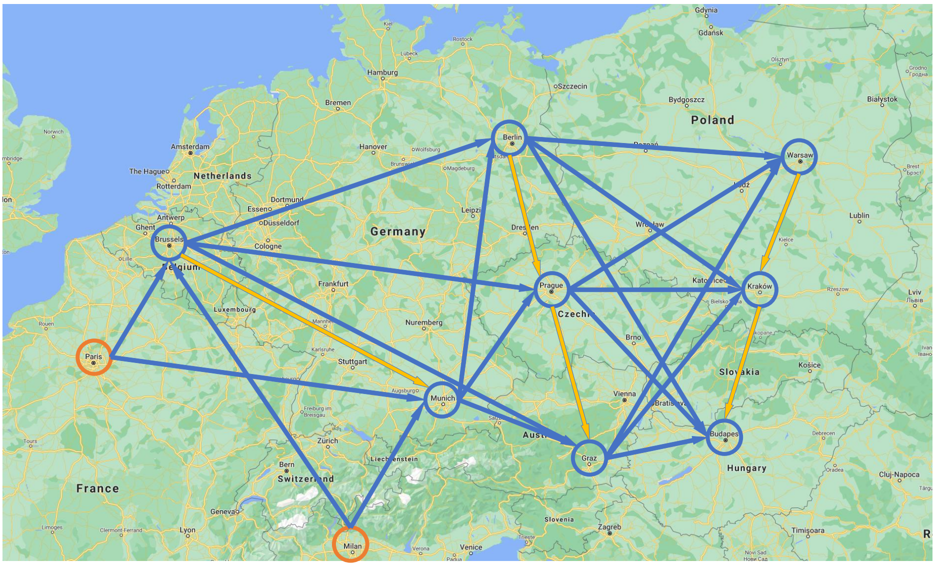

Figure 5: Transportation Network A.
Red circles denote the external suppliers in Paris and Milan.

The initial channel assignment for Network A

$$\Delta_{init} = \begin{bmatrix} 0 & 0.(3) & 0.5 & 0 & 0 & 0.(3) & 0.(3) & 0 \\ 0 & 0 & 0.5 & 0 & 0 & 0.(3) & 0.(3) & 0 \\ 0 & 0 & 0 & 0.(3) & 0.25 & 0 & 0.(3) & 0.25 \\ 0 & 0 & 0 & 0 & 0.25 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0.25 \\ 0 & 0 & 0 & 0.(3) & 0.25 & 0 & 0 & 0.25 \\ 0 & 0 & 0 & 0.(3) & 0.25 & 0.(3) & 0 & 0.25 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0.5 & 0.(3) & 0 & 0 & 0 & 0 & 0 & 0 \\ 0.5 & 0.(3) & 0 & 0 & 0 & 0 & 0 & 0 \end{bmatrix} \tag{12}$$

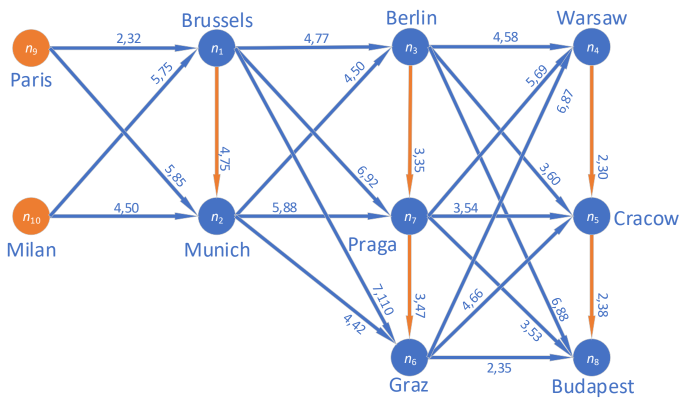

Figure 6: Transportation Network A - graph representation.
The arrows denote the goods flow direction, the orange ones denote lateral connections within the same layer. The numbers reflect β_{ji} and φ_{ij}.

and optimal one

$$\Delta_{opt} = \begin{bmatrix} 0 & 0.01 & 0.49 & 0 & 0 & 0.56 & 0.48 & 0 \\ 0 & 0 & 0.51 & 0 & 0 & 0.42 & 0.32 & 0 \\ 0 & 0 & 0 & 0.27 & 0.11 & 0 & 0.2 & 0.1 \\ 0 & 0 & 0 & 0 & 0.04 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0.75 & 0 & 0 & 0.03 \\ 0 & 0 & 0 & 0.61 & 0.1 & 0 & 0 & 0.69 \\ 0 & 0 & 0 & 0.12 & 0 & 0.02 & 0 & 0.18 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0.99 & 0.01 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0.01 & 0.98 & 0 & 0 & 0 & 0 & 0 & 0 \end{bmatrix} \tag{13}$$

The BBO algorithm notably modified the lot partitioning coefficients for the controlled nodes. The average cost function minimization in Network A of 14.77% allows one to throttle down the BE by 8.44% and diminish the transportation costs by 23.11%. Logistic networks with a denser topology (a bigger number of links per node) can be notably improved, both for transportation costs and the BE. With equal channel utilization, the BE is measured as 3.91 and transportation costs as 5.28 x 10^5 €. The BBO allowed decreasing the BE to 3.58 and transportation costs to 4.06 x 10^5 €.

The dependence of the population size and the maximum number of epoch required to accomplish a similar optimization result is displayed in Table 1. The

Table 1: Population size dependence

Population size *g*	ω_{min}	Ψ_{min} (€)	convergence time (s)
2	4.06	4.62 x 10^5	21.43
5	3.82	4.08 x 10^5	27.19
7	3.88	4.06 x 10^5	46.31
10	**3.58**	4.06 x 10^5	52.28
14	4.02	**4.03 x 10^5**	72.54

displayed values are the means from multiple simulation runs performed to leverage the BBO inherent randomness (sometimes the best solution has already been found in a few initial iterations). Fig. 7 illustrates the fitness function improvement value successive BBO iterations. The graph shows that the fitness function grows fast during the first few iterations and then progresses approximately linearly. Since the optimal solution is not known *a priori*, the stopping condition is enforced by a predefined maximum epoch number. Fig. 8 shows the BE evolution at the controlled nodes for the initial and final (optimum) transportation channel allocation. One can notice from the graph that the BBO algorithm successfully throttles down the BE. Besides, the transportation costs are reduced, having complete customer satisfaction.

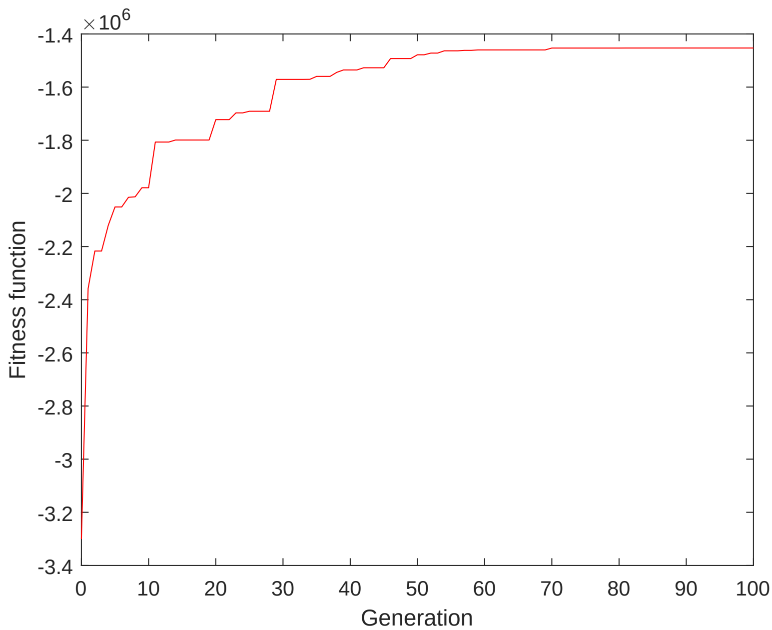

Figure 7: Fitness adjustment progress.

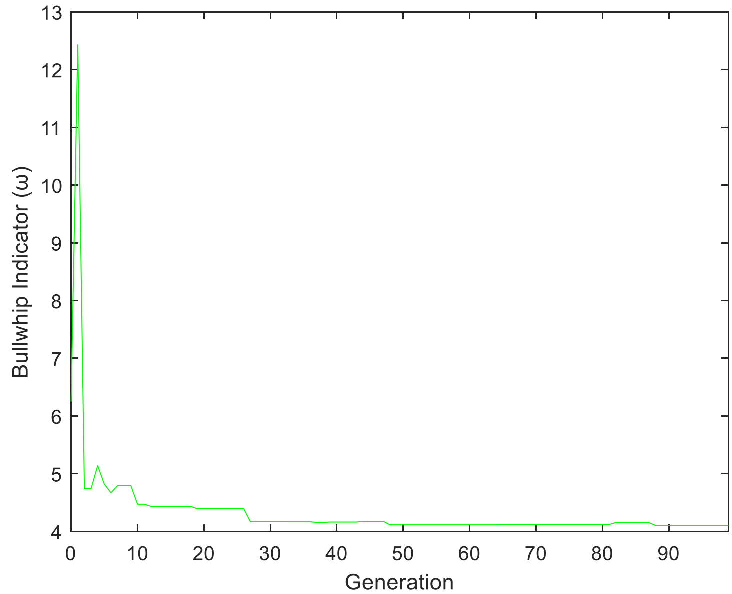

Figure 8: The BE evolution progress.

6. Conclusions

The paper investigates BBO implementation for the optimization of complex logistic networks governed by the OUT policy. The optimization objective is to diminish the transportation costs and avoid the BE, yet ensure high customer satisfaction. It is accomplished by modifying the allocation of the transportation channels. The fitness function of BBO has been defined so as to establish a smooth balance between the transportation costs (financial measure), the BE (logistic measure), and customer satisfaction. The population size happens to have a crucial impact on the BBO operation and convergence time. The amount of individuals in a population is proportional to the time of the optimal solution finding.
Nevertheless, by expanding the population size, the number of calculations and memory usage in every iteration grows. The numerous tests performed on a real-world transportation network indicate that the application of BBO for logistic networks optimization is advisable. Contrary to the full-search method, the desired balance between transportation cost reduction, systemic distortion alleviation, and elevating customer satisfaction can be achieved in a reasonable time frame using ordinary computers.

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References

[1] Horoshko, O. I., Horoshko, A., Bilyuga, S., and Horoshko, V. Theoretical and methodological bases of the study of the impact of digital economy on world policy in 21 century. *Technological Forecasting and Social Change*, 166:120640, 2021. doi:10.1016/j.techfore.2021.120640.

[2] Sumukadas, N. Are you ready for your next product recall crisis? Lessons from operations and supply chain management. *Business Horizons*, 64(2):211–221, 2021. doi:10.1016/j.bushor.2020.12.001.

[3] Grazia Speranza, M. Trends in transportation and logistics. *European Journal of Operational Research*, 264(3):830–836, 2018. doi:10.1016/j.ejor.2016.08.032.

[4] Lee, H., Padmanabhan, V., and Whang, S. The bullwhip effect in supply chains. *Sloan Management Review*, 38(3):93–102, 1997.

[5] Axsäter, S. *Inventory control*. Springer International Publishing, 2015.

[6] Naim, M. M., Spiegler, V. L., Wikner, J., and Towill, D. R. Identifying the causes of the bullwhip effect by exploiting control block diagram manipulation with analogical reasoning. *European Journal of Operational Research*, 263(1):240–246, 2017. doi:10.1016/j.ejor.2017.05.014.

[7] Lin, W. J., Spiegler, V. L., and Naim, M. M. Dynamic analysis and design of a semiconductor supply chain: a control engineering approach. *International Journal of Production Research*, 56(13):4585–4611, 2018. doi:10.1080/00207543.2017.1396507.

[8] Shaban, A. and Shalaby, M. A. Modeling and optimizing of variance amplification in supply chain using response surface methodology. *Computers and Industrial Engineering*, 120:392–400, 2018. doi:10.1016/j.cie.2018.04.057.

[9] Gupta, S. and Saxena, A. Classification of operational and financial variables affecting the bullwhip effect in Indian sectors: A machine learning approach. *Recent Patents on Computer Science*, 12(3):171–179, 2018. doi:10.2174/2213275911666181012121059.

[10] Boccadoro, M., Martinelli, F., and Valigi, P. Supply chain management by H-infinity control. *IEEE Transactions on Automation Science and Engineering*, 5(4):703–707, 2008. doi:10.1109/TASE.2008.917152.

[11] Ignaciuk, P. Nonlinear inventory control with discrete sliding modes in systems with uncertain delay. *IEEE Transactions on Industrial Informatics*, 10(1):559–568, 2014. doi:10.1109/TII.2013.2278476.

[12] Ignaciuk, P. Discrete inventory control in systems with perishable goods - A time-delay system perspective. *IET Control Theory and Applications*, 8(1):11–21, 2014. doi:10.1049/iet-cta.2013.0636.

[13] Bartoszewicz, A. and Latosinski, P. Reaching law based discrete time sliding mode inventory management strategy. *IEEE Access*, 4:10051–10058, 2016. doi:10.1109/ACCESS.2016.2633618.

[14] Dominguez, R., Cannella, S., and Framinan, J. M. The impact of the supply chain structure on bullwhip effect. *Applied Mathematical Modelling*, 39(23-24):7309–7325, 2014. doi:10.1016/j.apm.2015.03.012.

[15] Ignaciuk, P. and Wieczorek, Ł. Continuous genetic algorithms in the optimization of logistic networks: Applicability assessment and tuning. *Applied Sciences (Switzerland)*, 10(21):1–24, 2020. doi:10.3390/app10217851.

[16] Ignaciuk, P. and Wieczorek, Ł. Minimum fuel resource distribution in multidimensional logistic networks governed by base-stock inventory policy. In *Advances in Intelligent Systems and Computing*, volume 1196 AISC, pages 1141–1151. Springer, 2020. doi:10.1007/978-3-030-50936-1_95.

[17] Arbex, R. O. and da Cunha, C. B. Efficient transit network design and frequencies setting multi-objective optimization by alternating objective genetic algorithm. *Transportation Research Part B: Methodological*, 81:355–376, 2015. doi:10.1016/j.trb.2015.06.014.

[18] Tikani, H. and Setak, M. Efficient solution algorithms for a time-critical reliable transportation problem in multigraph networks with FIFO property. *Applied Soft Computing Journal*, 74:504–528, 2019. doi:10.1016/j.asoc.2018.10.029.

[19] Bielli, M., Caramia, M., and Carotenuto, P. Genetic algorithms in bus network optimization. *Transportation Research Part C: Emerging Technologies*, 10(1):19–34, 2002. doi:10.1016/S0968-090X(00)00048-6.

[20] Chew, J. S., Lee, L. S., and Seow, H. V. Genetic algorithm for biobjective urban transit routing problem. *Journal of Applied Mathematics*, 2013, 2013. doi:10.1155/2013/698645.

[21] Simon, D. Biogeography-based optimization. *IEEE Transactions on Evolutionary Computation*, 12(6):702–713, 2008. doi:10.1109/TEVC.2008.919004.

[22] Simon, D. A dynamic system model of biogeography-based optimization. *Applied Soft Computing Journal*, 11(8):5652–5661, 2011. doi:10.1016/j.asoc.2011.03.028.

[23] Yang, G. and Liu, Y. Optimizing an equilibrium supply chain network design problem by an improved hybrid biogeography based optimization algorithm. *Applied Soft Computing Journal*, 58:657–668, 2017. doi:10.1016/j.asoc.2017.05.023.

[24] Zhang, S., Xu, S., Zhang, W., Yu, D., and Chen, K. A hybrid approach combining an extended BBO algorithm with an intuitionistic fuzzy entropy weight method for QoS-aware manufacturing service supply chain optimization. *Neurocomputing*, 272:439–452, 2018. doi:10.1016/j.neucom.2017.07.011.

[25] Roozbeh Nia, A., Hemmati Far, M., and Akhavan Niaki, S. T. A fuzzy vendor managed inventory of multi-item economic order quantity model under shortage: An ant colony optimization algorithm. *International Journal of Production Economics*, 155:259–271, 2014. doi:10.1016/j.ijpe.2013.07.017.

[26] Xin, X., Jiang, Q., Li, S., Gong, S., and Chen, K. Energy-efficient scheduling for a permutation flow shop with variable transportation time using an improved discrete whale swarm optimization. *Journal of Cleaner Production*, 293, 2021. doi:10.1016/j.jclepro.2021.126121.

[27] Ignaciuk, P. and Dziomdziora, A. Bullwhip Effect - Supply Chain Stability Examination in the Presence of Demand Uncertainty and Delay. In *2020 24th International Conference on System Theory, Control and Computing, ICSTCC 2020 - Proceedings*, pages 624–629. IEEE, 2020. doi:10.1109/ICSTCC50638.2020.9259768.

[28] Kamhuber, F., Sobottka, T., Heinzl, B., Henjes, J., and Sihn, W. An efficient hybrid multi-criteria optimization approach for rolling production smoothing of a European food manufacturer. *Computers and Industrial Engineering*, 147, 2020. doi:10.1016/j.cie.2020.106620.

[29] Ignaciuk, P. and Wieczorek, Ł. Networked base-stock inventory control in complex distribution systems. *Mathematical Problems in Engineering*, 2019:1–14, 2019. doi:10.1155/2019/3754367.

[30] Chen, F., Drezner, Z., Ryan, J. K., and Simchi-Levi, D. Quantifying the bullwhip effect in a simple supply chain: the impact of forecasting, lead times, and information. *Management Science*, 46(3):436–443, 2000. doi: 10.1287/mnsc.46.3.436.12069.

[31] Ignaciuk, P. and Dziomdziora, A. Quantifying the bullwhip effect in networked structures with nontrivial topologies. In *ACM International Conference Proceeding Series*, pages 62–66. Association for Computing Machinery, New York, NY, USA, 2020. doi:10.1145/3437075.3437092.