Intelligent Planning of Logistic Networks to Counteract Uncertainty Propagation

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Abstract. A major obstacle to stable and cost-efficient management of goods distribution systems is the bullwhip effect – reinforced demand uncertainty propagating among system nodes. In this work, by solving a formally established optimization problem, it is shown how one can mitigate the bullwhip effect, at the same minimizing transportation costs, in modern logistic networks with complex topologies. The flow of resources in the analyzed network is governed by the popular order-up-to inventory policy, which thrives to maintain sufficient stock at the nodes to answer *a priori* unknown, uncertain demand. The optimization objective is to decide how intensive a given transport channel should be used so that unnecessary goods relocation and the bullwhip effect are avoided while being able to fulfill demand requests. The computationally challenging optimization task is solved using a population-based evolutionary technique – Biogeography-Based Optimization. The results are verified in extensive simulations of a real-world transportation network.

Keywords: Transportation Networks, Time-Delay Systems, Population-Based Optimization

1 Introduction

The bullwhip effect (BE) is a serious systemic distortion in logistic systems, manifesting itself as an enhanced variability of demand transmitted into the goods ordering signal. In addition to lowered earnings, it leads to unnecessary shipments, prolonged delays, and resource accumulation at subsidiary nodes. Thus far, its impact has been assessed primarily from local and chain-structure perspectives. In contrast, here, the BE formation and countermeasures are investigated in the context of modern networked systems, not restricted to specific, reduced topologies.

Forrester laid grounds for the BE examination in [1], with continued studies related to its formation within production-distribution environments reported later in [2]–[4]. The principal factors affecting the goods flow fluctuation in basic architectures were discussed by Lee et al. in [5] and [6], and in current settings in [7]–[9]. The essential BE triggers include: inaccurate demand prediction, production rate mismatch, non-negligible transportation time, batch arrangement, and price variations. A comprehen-

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sive classification of the BE causes in modern systems is given by Lin et al. in [10], with focalized treatment of erroneous stock level records in [11].

Besides seeking its origins, many scientists worked on techniques of decreasing the negative impact of the BE on supply system performance [12]–[15]. They emphasized statistical analysis and operations research methods. Another promising approach was to apply robust control techniques [16]–[19]. However, in practical installations, traditional methods are still preferred, e.g., order-up-to (OUT) policy. The BE formation in the systems organized in serial and arborescent configurations governed by the OUT policy has been examined in [20]. Preliminary treatment of mesh-type topologies has been given in [21]. A modified OUT policy, destined for centralized system management, was optimally tuned for holding and lost-sales costs reduction in [22].

In real-world logistic systems, the optimization typically targets delays and holding or transportation costs reduction. Finding the optimal solution for the considered objective functions, either analytically or numerically (e.g., through full search), is challenging. Therefore, non-weighted procedures, e.g., alternating, hierarchical, or phased optimization techniques, are applied. For example, to minimize both the whole-time cost of travelers and the number of essential transfers in a transit system, Arbex and da Cunha [23] introduced Alternating Objective Genetic Algorithm. As opposed to the traditional one [24], [25], it allowed them to use local search methods to deal with infeasibility of newly created individuals. Also, improved Simulated Annealing has recently been considered in the optimization of transportation networks [26]. However, the applied objectives overlook a fundamental problem that face modern systems: to work efficiently in a time-varying, perturbed environment. Hence, in this work, the OUT policy optimization explicitly targets reduction of a systemic distortion – the BE.

The considered class covers systems with an arbitrary configuration, with goods reflow subjected to non-negligible time delay. The popular OUT inventory policy governs lot sizing. The objective is to plan the network structure, i.e., to decide how intensively a given transportation route (channel) of goods distribution should be used to avoid the BE. As a result, a matrix of coefficients yielding reduced BE and transportation costs within a given time horizon is obtained. The coefficients may also be interpreted in terms of order splitting, i.e., which part of an order established by a controlled node is to be retrieved from a given supplier (a nearby controlled node or an external source). The optimization task is solved with one of recent evolutionary techniques – Biogeography-Based Optimization (BBO). The acquired tuning guidelines for the coefficient adjustment are straightforward in implementation and do not require considerable computational effort to calculate. As shown in the conducted research, the commonly exercised omission of the planning aspect through uniform lot partitioning among the transport channels is incorrect since it leads to reinforced perturbation and larger costs. The proposed intelligent planning technique enables one to place the goods distributor in a desirable situation with respect to the competition, reduces transportation costs, and throttles down the BE within the system.

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2 Bullwhip effect in transportation networks

An example supply chain is illustrated in Fig.1, with S_1 – the external supplier, u_1, u_2, …, u_i – ordering signals, and d_1, d_2, …, d_i – imposed demands.

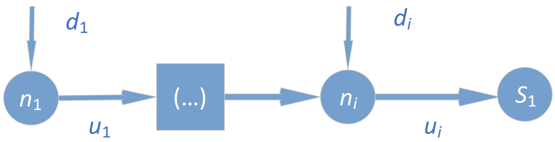

Fig. 1. Serial connection of *n* nodes. Resources are supplied by external source S_1. The arrows reflect the flow of information.

In [27], several indicators used to quantify the BE in serial structures, both in the time and the frequency domain, have been examined. One of the most popular ones is the order-to-demand variance ratio [28]. At node *i*, this bullwhip indicator (BI) is calculated as:

$$b_i = \frac{\text{var}[u_i]}{\text{var}[d_i]}, \tag{1}$$

where var[·] denotes variance. Value $b_i > 1$ means that at echelon *i*, the BE has been triggered.

In the nominal operating conditions, the OUT policy guarantees that for any demand pattern

$$b_1 = b_2 = \ldots = b_n = 1, \tag{2}$$

and the BE is absent [18].

Assuming that signals d_1, …, d_i are not correlated (given the knowledge about the demand imposed at a node, one should in principle not judge about the demand at other nodes), the BI can be measured having both internal and external demand incorporated as:

$$b_i = \frac{\text{var}[u_i]}{\text{var}[d_i + u_{i-1}]} = \frac{\text{var}[u_i]}{\text{var}[d_i] + \text{var}[u_{i-1}]}. \tag{3}$$

Nonetheless, to estimate the system propensity to the BE formation in current systems, one should examine more involving topologies than a serial chain. An example *networked* structure is illustrated in Fig. 2, where $n_{1–3}$ denote controlled nodes, $S_{1.2}$ are external sources, and $d_{1–3}$ is the exogenous demand imposed on the system.

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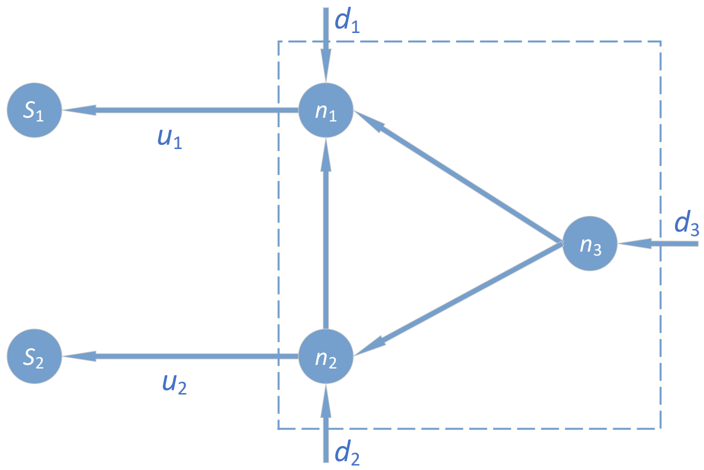

Fig. 2. A five-node transportation network.

In the system from Fig. 2, intuitively, the BE will be triggered when variance increase between the external replenishment signal $\mathbf{u} = [u_1\ u_2]^{\mathrm{T}}$ and the imposed demand $\mathbf{d} = [d_1\ d_2\ d_3]^{\mathrm{T}}$ is observed. Unlike the serial structure, the BI takes a matrix form – **B** – determined from the relation:

$$\begin{bmatrix} \mathrm{var}[u_1] \\ \mathrm{var}[u_2] \end{bmatrix} = \underbrace{\begin{bmatrix} b_{11} & b_{12} & b_{13} \\ b_{21} & b_{22} & b_{23} \end{bmatrix}}_{\mathbf{B}} \begin{bmatrix} \mathrm{var}[d_1] \\ \mathrm{var}[d_2] \\ \mathrm{var}[d_3] \end{bmatrix}. \tag{4}$$

It is evident, that the application of indicators for serial connection is not sufficient to quantify the BE in a networked configuration, even in the basic setting from Fig. 2. Moreover, equation (2) does not hold in the networked case. Different measures are thus needed.

As opposed to the serial configuration, in which one may directly indicate the marginal nodes and use them to establish a BI within the transportation system, there is a limited possibility to adopt such approach in a networked environment. The absence of feasible measurement methods, providing the BE quantification in networked systems, motivates the search for alternatives [29]. The introduced indicator should allow the BE quantification, considering the networked topology as a holistic, multi-input multi-output entity. Hence, it shall relieve the complexity of determining each entry of matrix **B**. For the BE quantification in networked structures, a vector-based measure will be defined.

Instead of focusing on a particular node, all the demand and external replenishment signals will be considered. Within horizon of H periods, the record of replenishment signal placed by node i at an external supplier $u_i^H = [u_i(0)\ u_i(1)\ \ldots\ u_i(H–1)]^{\mathrm{T}}$. Similarly with respect to demand placed at node j one has $d_j^H = [d_j(0)\ d_j(1)\ \ldots\ d_j(H–1)]^{\mathrm{T}}$. The demand can be imposed on any node. Also, any node can generate a replenishment

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signal for an external supplier. The proposed BI, associated with the Euclidean distance, is calculated as:

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

where Ω_e is the set of node indices that generate replenishment signals for the external suppliers, and Ω_d is the set of node indices at which the demand is placed.

With respect to the external actors, the controlled network is treated as a black-box entity. $\omega > 1$ implies an occurrence of the BE. The bigger the value of ω, the worse the BE.

3 System model

3.1 Interconnection structure

The considered class of system covers interaction between two types of actors:

- external sources – which supply the goods for the controlled network, yet are not affected by the customer demand, directly,
- controlled nodes – which serve both as intermediate suppliers for other controlled nodes and generate replenishment signals for the external sources to meet the demand.

The network encompasses N controlled nodes and S external sources, connected by unidirectional links. The links are characterized by:

- lot partitioning coefficient – to be determined in the optimization tasks – that says how intensively a given link (transportation channel) will be used,
- lead-time delay – the delay in order fulfillment, notably, the transport delay,
- transportation cost – related to the distance between the nodes.

For practical reasons, topologies with isolated nodes, i.e., having no connection to any supplier; or self-suppling nodes, are disregarded.

3.2 Node dynamics

Let $k = 0, 1, 2, \ldots, H$ measure the duration of time. The stock level of goods accumulating at node i evolves according to

$$x_i(k+1) = x_i(k) + \underbrace{\sum_{j=1}^{N+S} \alpha_{ji} u_i(k-\beta_{ji})}_{\text{incoming shipments}} - \underbrace{\sum_{j=1}^{N} \alpha_{ij} u_i(k)}_{\text{outgoing shipments}} - \underbrace{d_i(k)}_{\text{customer demand}} \quad (6)$$

where:

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- α_{ji} – the lot partitioning coefficient for the orders placed by node i at node j,
- β_{ji} – the lead-time delay of goods transferred from node j to i,
- $u_i(k)$ – the goods quantity requested by the node i in period k from its suppliers, both external sources and intermediate nodes,
- $d_i(k)$ – the external demand imposed on node i in period k. It exhibits arbitrary variations within $[0, d_i^{\max}]$, where $d_i^{\max}$ is the upper estimate.

The channel allocation matrix groups lot partitioning coefficients:

$$\mathbf{A} = \begin{bmatrix} 0 & \alpha_{12} & \cdots & \alpha_{1N} \\ \alpha_{21} & 0 & \cdots & \alpha_{2N} \\ \vdots & \vdots & \ddots & \vdots \\ \alpha_{N1} & \alpha_{N2} & \cdots & 0 \\ \vdots & \vdots & \cdots & \vdots \\ \alpha_{N+S,1} & \alpha_{N+S,2} & \cdots & \alpha_{N+S,N} \end{bmatrix}_{N+S\times N}, \tag{7}$$

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

$$0 \le \alpha_{ji} \le 1 \text{ and } \sum_{j=1}^{N+S} \alpha_{ji} = 1. \tag{8}$$

3.3 OUT inventory policy

To manage the flow of resources in the network, the OUT inventory policy is applied. It is implemented in a distributed form, i.e., independently at the controlled nodes. According to the OUT policy, controlled node i generates the stock replenishment signal as

$$u_i(k) = x_i^{ref} - x(k) - OR_i(k), \tag{9}$$

where x_i^{ref} is the reference level, e.g., that can be assigned to maximize sales [30], and $OR_i(k)$ is the open-order quantity, i.e., the goods in transit that have not yet reached the ordering node owing to lead-time delay.

3.4 Transportation Costs

The transportation costs are calculated by considering the length of the transportation trail and the quantity of the goods requested. Within the time horizon of H periods transportation cost

$$\Psi = \sum_{k=0}^{H-1} \sum_{i=1}^{N} \sum_{j=1}^{N+S} \alpha_{ji} u_i(k) \varphi_{ji} \phi \tag{10}$$

where φ_{ij} is the transportation cost along the route i-j determined as a product of a fixed unitary cost φ and the distance between the nodes.

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3.5 Customer satisfaction

A well-functioning goods distribution system is expected to ensure a high level of demand satisfaction. Denoting the satisfied demand at controlled node *i* in period *k* by $h_i(k)$, the customer satisfaction rate at that node is obtained as

$$\varepsilon_i = \frac{\sum_{k=0}^{H-1} h_i(k)}{\sum_{k=0}^{H-1} d_i(k)}, \tag{11}$$

An average satisfaction rate within the system can be calculated as

$$\vartheta = \frac{\sum_{i=1}^{N} \varepsilon_i}{N}. \tag{12}$$

4 Optimization problem

The objective of the considered optimization problem is to establish a channel allocation matrix (7) so that the logistic system may satisfy the external demand with low transportation costs, yet avoiding the BE.

Formally, the optimization problem may be stated as follows:

$$\min J(\alpha_{ij}) = \mathbf{\Psi}(k)\omega\vartheta^{-1}. \tag{13}$$

s.t. (6) – the stock level dynamics, (8) – the channel allocation constraint, and (9) – the method of replenishment signal computation. ω stands for the introduced BI for networked systems, Ψ is the transportation cost, and ϑ represents the mean customer satisfaction rate. Thus, one attempts to balance transportation costs and systemic distortion, at the same time maintaining a high customer service rate.

In the analyzed class of systems, the demand signal varies with time in an unpredictable way. Consequently, optimization problem (13) is not amenable to analytical treatment. It will be solved using a computational intelligence technique, specified in the next chapter.

5 Computational framework

As a basis for constructing a computation framework to solve problem (13), a biogeography-based technique – BBO – will be adopted. BBO is an evolutionary algorithm that originates from the observations of the movement of species among separate areas called islands. It has been demonstrated to be a useful search procedure in optimization problems because it combines both examination and exploitation techniques based on migration [31]. Nowadays, it is one of the fastest growing in popularity algorithms, based on nature, used to tackle computationally-intensive optimization problems. In addition to numerous benefits, such as simplicity, flexibility, and effi-

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ciency, BBO does not demand computing derivatives of objective function. Its dynamic model has been described in [32]. The BBO algorithm is illustrated in Fig. 3.

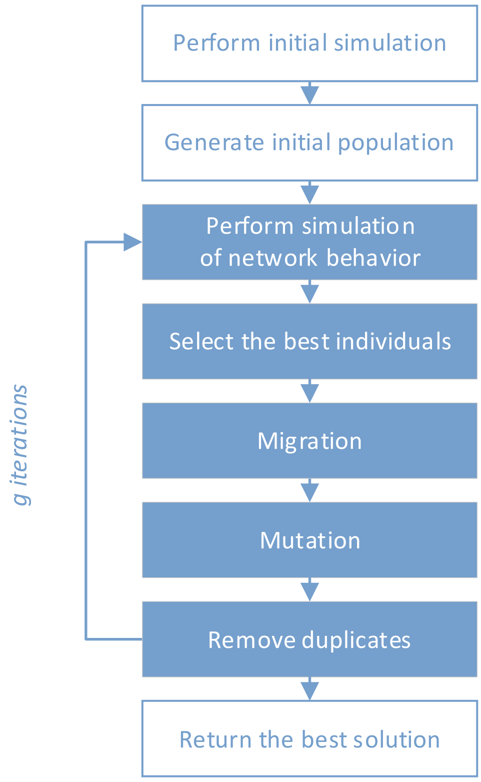

Fig. 3. BBO algorithm flowchart.

In evolutionary approaches, global recombination is applied to generate new solutions. However, in BBO it is migration that modifies existing solutions. The continuous domain of the search space allows for direct BBO application, i.e., without the classic translation to the binary form [24]. The matrix of lot partitioning coefficients reflects an individual, and an island (a set of individuals) corresponds to the set of a predefined size containing matrices of lot partitioning coefficients. A particular population comprises a set of islands. The component of an individual corresponds to a single lot partitioning coefficient – α_{ij} – in matrix **A**.

If a solution is intended for mutation, then a randomly chosen lot partitioning coefficient may be replaced with a newly generated one. The matrix of lot partitioning coefficients is created by randomly mutating the current columns, one-by-one, before going to a next algorithm iteration. It is performed by randomly increasing or decreasing each entry – α_{ij} – in the column. The value of the last entry in column j is calculated as $1-\sum_{i=1}^{N+S-1}\alpha_{ji}$.

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6 Numerical studies

The system considered in the numerical study represents the European distribution network of a firm from the premium-clothes fashion industry. The company root warehouses are located in Paris and Milan. The sales network extends through Central Europe, with the distribution centers in Brussels, Munich, Berlin, Warsaw, and Cracow, as illustrated in Fig. 4. The network graph representation is depicted in Fig. 5. The numbers displayed above the arrows indicate the lead-times and transportation costs associated with the routes.

Two cases (Network A and B) are given a closer examination. First, the star-network (Fig. 4), as the centralized architecture representation, is investigated. Afterward, a more complex topology, reflecting worldwide expansion, is investigated. In that case, additional sales points are introduced – with locations in Graz, Prague, and Budapest, as shown in Fig. 6. The graph representation of Network B is shown in Fig. 7.

The objective is to find the optimal lot partitioning coefficients for controlled nodes to minimize both the BE and transportation costs. Initially, the lot partitioning is distributed evenly among the connected nodes, as is customary in the literature. The simulation horizon is set as 10^3 periods. The demand, imposed on all the controlled nodes, exhibits stochastic variations generated according to the Poisson distribution with $\lambda = 0.6$. The unitary transportation cost equals $\phi = 0.04$ € per 10 km. Network A encompasses 7 nodes ($N = 5$, $S = 2$), which leads to 1.07×10^4 candidate solutions to perform a full-search with granularity 0.01. Network B comprised 10 nodes ($N = 8$, $S = 2$), with a search space of 6.54×10^{28} possible solutions, which is thus no longer viable for a full search. Therefore, the BBO method is applied. Each population in the BBO algorithm contains 10 individuals. The maximum number of generations is set as $g = 50$ epochs. Additional mutations are not applied in updating the emigration rates.

Fig. 4. Transportation network A.
Red circles indicate external suppliers located in Paris and Milan.

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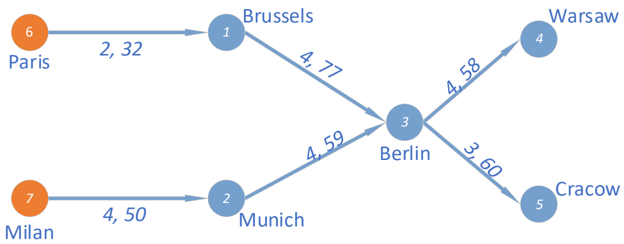

Fig. 5. Transportation network A –graph representation.
The arrows indicate the goods flow direction. The numbers denote α_{ij} and φ_{ij}.

Network A shows an unstable behavior, reflected in the BE > 1. The lot partitioning coefficients modification in the considered distribution network has a minimal impact on the BE and transportation costs. The initial channel assignment and the best-obtained solution are

$$\mathbf{A} = \begin{bmatrix} 0 & 0 & 0.5 & 0 & 0 \\ 0 & 0 & 0.5 & 0 & 0 \\ 0 & 0 & 0 & 1 & 1 \\ 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 \\ 1 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 \end{bmatrix} \rightarrow \begin{bmatrix} 0 & 0 & 0.23 & 0 & 0 \\ 0 & 0 & 0.77 & 0 & 0 \\ 0 & 0 & 0 & 1 & 1 \\ 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 \\ 1 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 \end{bmatrix} \quad (14)$$

Before the optimization process, the BE is quantified as 2.58 and transportation costs as 2.05 x 10^5 €. Conducted optimization slightly improved overall performance by decreasing the BE to 2.57 and transportation costs value to 2.04 x 10^5 €, i.e., by 0.5%. Hence, the considered star-network leaves little room for optimization due to the limited number of lot partitioning coefficient modifications available in preordained interconnection structure.

The second investigated network, with a more complex topology, revealed factors that are non-negligible to the BE formation, i.e., the number of connections per node (ϑ = 2.3) and the overall number of echelons (τ = 10). The BBO algorithm significantly modified the lot partitioning coefficients for the controlled nodes. For Network B having 8 controlled nodes, the average cost function minimization of 24.48% enables one to bring down the BE by 24.86% and the transportation costs by 24.11%. Distribution networks with a denser topology (a bigger number of connections per node) give more space for improvement, both with respect to transportation costs and the BE. With even channel utilization, the BE is quantified as 1.73 and transportation costs as 5.06 x 10^5 €. The BBO allowed reducing the BE to 1.3 and transportation costs to 3.84 x 10^5 €.

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Fig. 6. Transportation network B.
Red circles indicate the external suppliers located in Paris and Milan.

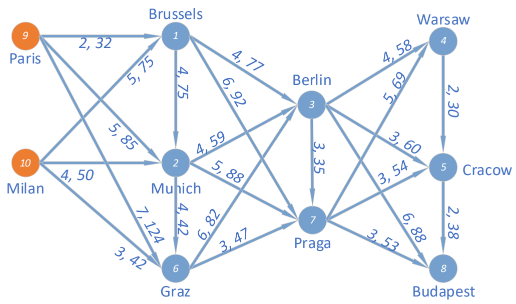

Fig. 7. Transportation network B – graph representation.
The arrows indicate the goods flow direction. The numbers denote α_{ij} and φ_{ij}.

The initial channel assignment for network B

$$\mathbf{A}_{init} = \begin{bmatrix} 0 & 0.34 & 0.34 & 0 & 0 & 0 & 0.25 & 0 \\ 0 & 0 & 0.33 & 0 & 0 & 0.34 & 0.25 & 0 \\ 0 & 0 & 0 & 0.5 & 0.34 & 0 & 0.25 & 0.34 \\ 0 & 0 & 0 & 0 & 0.33 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0.33 \\ 0 & 0 & 0.33 & 0 & 0 & 0 & 0.25 & 0 \\ 0 & 0 & 0 & 0.5 & 0.33 & 0 & 0 & 0.33 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0.5 & 0.33 & 0 & 0 & 0 & 0.33 & 0 & 0 \\ 0.5 & 0.33 & 0 & 0 & 0 & 0.33 & 0 & 0 \end{bmatrix} \quad (15)$$

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and optimal one

$$\mathbf{A}_{opt} = \begin{bmatrix} 0 & 0.01 & 0.30 & 0 & 0 & 0 & 0.64 & 0 \\ 0 & 0 & 0.34 & 0 & 0 & 0.01 & 0.32 & 0 \\ 0 & 0 & 0 & 0.17 & 0.25 & 0 & 0.01 & 0.08 \\ 0 & 0 & 0 & 0 & 0.08 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0.43 \\ 0 & 0 & 0.36 & 0 & 0 & 0 & 0.03 & 0 \\ 0 & 0 & 0 & 0.83 & 0.67 & 0 & 0 & 0.49 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0.99 & 0.01 & 0 & 0 & 0 & 0.01 & 0 & 0 \\ 0.01 & 0.98 & 0 & 0 & 0 & 0.98 & 0 & 0 \end{bmatrix} \quad (16)$$

7 Conclusions

The paper introduced a method of counteracting a major systemic distortion in distribution networks – the bullwhip effect – through an appropriate transportation channel assignment. A nontrivial multi-echelon topology, with arbitrary interconnection structure and time-delayed good relocation, is considered. The channel allocation is obtained via a formally stated optimization problem, solved using a population-based evolutionary technique – BBO. BBO allows one to circumvent the computational intricacy related to random demand and a dimensionality obstacle originating from the retarded argument in the network dynamical description. The allocation method allows for both the BE and transportation costs reduction. The validity is verified via numerical tests conducted for an example real-world transportation network. In a further study, other than OUT inventory policies will be considered and more elaborate tuning procedures covering sensitivity and robustness aspects.

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