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Intelligent Support for Resource Distribution in Logistic Networks Using Continuous-Domain Genetic Algorithms

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***Abstract*—The paper addresses the issue of improving the goods distribution efficiency in logistic networks subjected to uncertain demand. The class of networks under consideration encompasses two types of entities – controlled nodes and external sources – forming a mesh interconnection structure. In order to find the optimal operating conditions for the *a priori* unknown, time-varying demand, numerous, computationally involving simulations need to be conducted. In this work, the application of genetic algorithms (GAs) with continuous domain search is proposed to optimize the goods reflow in the network. The objective is to reduce the holding costs while ensuring high customer satisfaction. Using a network state-space model with a centralized inventory management policy, GA automatically adjusts the policy parameters to a given network topology. Extensive tests for different statistical distributions validate the analytical content.**

Keywords*—inventory management, optimization, genetic algorithms, uncertain demand.

I. Introduction

Despite the recent financial crisis, overall, the world economy has experienced an increasing growth rate in the last twenty years. New branches of industry and services have emerged and many of the existing ones have expanded even more than throughout the entire previous century [1, 2]. One of such well prospering fields is logistics, which involves planning and managing a cost efficient flow of raw materials, assembly parts, and finished products [3]. Moreover, logistics creates opportunities for the development of other sectors and facilitates their implementation.

Meanwhile, the use of intelligent methods gains in popularity in the applications beyond pure computer science [4–6]. Most companies gather a substantial amount of information from their customers and users. On the other hand, the growth of the related field – Internet of Things – makes new types of sensors and embedded systems commercially available and put into practice [7]. The collected data can be used in many innovative ways, in particular, to obtain more accurate information about the current state of transportation systems, supply chains, and networks. The next step is capturing more viable trends and obtaining predictions of the system future behavior to further boost the performance and alleviate the costs. For instance, the data retrieved from the GPS navigation devices allow one to determine the most appropriate path, or to estimate the traffic intensity on-the-fly to reduce the congestion and shorten the transfer time to the intended destination. Certain companies, such as Google, or TomTom, in their mobile mapping technology incorporate cameras and lasers mounted on the metering cars to create realistic 3D models of the urban areas for autonomous driving vehicles to be used in future logistic solutions [8].

Nevertheless, the scientific examination of modern distribution networks is a difficult task owing to the analytical intricacies and high mathematical complexity of realistic models. So far, the following types of simplified structures have received the primary attention:

- single-echelon systems [9–11],
- serial multi-echelon chains [12–14],
- star-bus networks [15–17].

With the pace of improvements in the current industry, it is necessary to address the design issues in more complex configurations that would respond well to the growing and more stringent customer expectations. In order to provide high-quality services, various resource management policies [18, 19] and heuristics [20, 21] are being formulated. However, they typically require sophisticated tuning mechanisms to reach a desired efficiency level. In this work, it is shown how to automatize such tuning process with respect to a centralized inventory management policy to be deployed in the logistic networks with arbitrary connectivity structure using genetic algorithms (GAs).

First, the considered strategy is described in the analytical terms. Then, it is adjusted to a given topology using a continuous GA. The optimization process objective is to achieve a balance between the customer satisfaction and the goods holding costs. The customer satisfaction is quantified as the fraction of fulfilled demand requests, whereas the holding costs are related to the number of excess goods stored at the controlled nodes during the distribution process. The implemented continuous-domain GA allows for fast, automatic policy adjustment to the specified requirements. Numerical studies prove the efficiency of GAs in solving optimization issues in non-trivial logistic system configurations.

II. Network Model

A. Network Structure and Node Behavior

The structure of the network under consideration comprises N controlled nodes and M resource suppliers. The connections among the nodes form a general, mesh-type topology. The uncertain customer demands are imposed on the controlled nodes at any instant throughout the distribution process execution. The controlled nodes have limited storage capacity and the external resource suppliers are uncapacitated. Although arbitrary connectivity is permitted in the model, there are no separate nodes in the structure (the network is connected), and no node can replenish itself (through a direct loop). The connection between two nodes i and j is characterized by a pair of attributes (DT_{ij}, SC_{ij}), in which:

- DT_{ij} – is the lead-time delay of a replenishment order coming from node i to j,
- SC_{ij} – is the contribution of the overall order issued by node i to be obtained from node j.

The operation sequence at a controlled node occurring in each period is illustrated in Fig. 1. At the beginning, the quantity of incoming shipments is registered into the stock. Afterwards, the node processes the customer demand requests and tries to fulfill them. Finally, the node focuses on maintaining the balance throughout the network by satisfying the replenishment orders issued by the other, directly connected nodes.

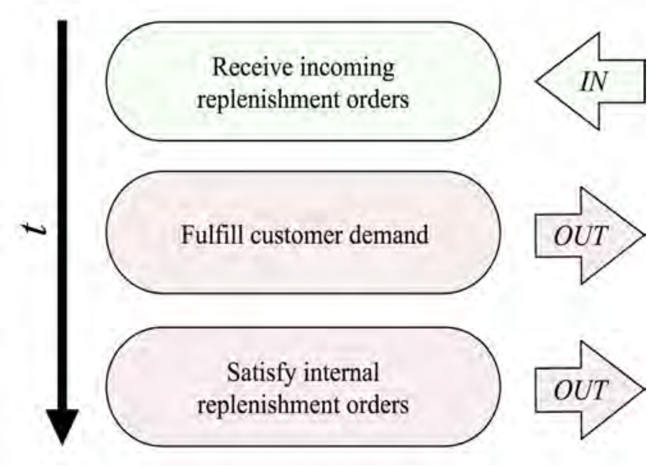

Fig. 1. Node operational sequence.

B. Model of Node Interaction

According to the routine of operations related to handling the flow of goods, the stock balance equation at controlled node i can by expressed through

$$l_i(t+1) = l_i(t) + \Omega_i^I(t) - d_i(t) - \Omega_i^O(t)\,, \tag{1}$$

where:

- $l_i(t)$ – is the on-hand stock level at time t, t = 0, 1, …
- $\Omega_i^I(t)$ – is the quantity of replenishment orders – incoming shipments – received by node i,
- $\Omega_i^O(t)$ – is the quantity of replenishment orders sent to the directly connected nodes,
- $d_i(t)$ – is the quantity of satisfied external demands.

According to [22], the incoming replenishment orders from the suppliers of node i can be calculated as

$$\Omega_i^I(t) = \sum_{j=1}^{N+M} \mu_{ji} o_i(t - \gamma_{ji})\,. \tag{2}$$

Similarly, the amount of shipments sent to the other nodes equals

$$\Omega_i^O(t) = \sum_{s=1}^{N} \mu_{is} o_s(t - \tau_i^P)\,. \tag{3}$$

In equations (2) and (3):

- μ_{ji} – denotes the supply fraction of the total replenishment order to be acquired from node j,
- o_i – is the total amount of goods requested from node i,
- γ_{ji} – represents the lead-time delay at the link between node j and i, $\gamma_{ji} \in \{1, \ldots, \Gamma\}$. In detail, $\gamma_{ji} = \tau_j^P + \tau_{ji}$, where τ_j^P is the shipment preparation time at node j and τ_{ji} is the transportation latency from node j to i. All the delays are expressed as non-negative integers.

C. State-Space Description

In order to perform numerical studies of the network behavior in a manageable way, a state-space model will be introduced as vector representation of node interactions. In the adopted framework, the goods distribution process proceeds according to

$$\boldsymbol{l}(t+1) = \boldsymbol{l}(t) + \sum_{\gamma=1}^{\Gamma} \boldsymbol{\Phi}_\gamma \boldsymbol{o}(t-\gamma) - \boldsymbol{d}(t)\,, \tag{4}$$

where:

- $\boldsymbol{l}(t)$ – is the vector of on-hand stock levels in period t,
- $\boldsymbol{o}(t)$ – is the vector of stock replenishment orders in period t,
- $\boldsymbol{d}(t)$ – is the vector of external demands in period t,
- $\boldsymbol{\Phi}_\gamma$ – denotes the matrix of node interconnections,

$$\boldsymbol{\Phi}_\gamma = \begin{bmatrix} \sum_{i:\Gamma_{i1}=\gamma} \mu_{i1} & x_{12} & \cdots & x_{1N} \\ x_{21} & \sum_{i:\Gamma_{i2}=\gamma} \mu_{i2} & \cdots & x_{2N} \\ \vdots & \vdots & \ddots & \vdots \\ x_{N1} & x_{N2} & \cdots & \sum_{i:\Gamma_{iN}=\gamma} \mu_{iN} \end{bmatrix}. \tag{5}$$

The entries on the main diagonal of matrix $\boldsymbol{\Phi}_\gamma$ represent the incoming shipments with lead-time delay γ. The off-diagonal entries are set as

$$x_{ik} = \begin{cases} -\mu_{ik}, \text{ if } \tau_i^P = \gamma, \\ 0, \text{ if } \tau_i^P \neq \gamma, \end{cases} \quad (6)$$

where $k \in \{1, \ldots, N\}$.

D. Networked Inventory Policy

For efficient performance, the networked inventory policy requires proper selection of target inventory levels (TILs), that should be adjusted for all the controlled nodes with respect to the external demand and network topology. The policy will try to maintain the stock at TIL in each period as the distribution process evolves. The quantity of replenishment orders issued by node *i* to its suppliers in period *t* is obtained from

$$\boldsymbol{o}(t) = \boldsymbol{\Phi}^{-1}\left[\boldsymbol{l}^T - \boldsymbol{l}(t) - \sum_{\gamma=1}^{\Gamma}\sum_{k=\gamma}^{\Gamma}\boldsymbol{\Phi}_\gamma \boldsymbol{o}(t-k)\right], \quad (7)$$

where:

- $\boldsymbol{l}^T$ – the vector of TILs for the controlled nodes,
- $\boldsymbol{\Phi}$ – a gain matrix holding the summary information about the network interconnections and delays,

$$\boldsymbol{\Phi} = \sum_{\gamma=1}^{\Gamma}\boldsymbol{\Phi}_\gamma \,. \quad (8)$$

According to [20], there exists a minimum TIL at the corresponding node beyond which full customer satisfaction is achieved. In order to calculate the TIL vector for the entire network, an estimate of the highest demand is needed. Assuming a persistent demand at each node, such TIL vector may be calculated as

$$\boldsymbol{l}^T = \left(\mathbf{I_N} + \sum_{\gamma=1}^{\Gamma}\gamma\boldsymbol{\Phi}_\gamma\right)\boldsymbol{\Phi}^{-1}\boldsymbol{d}_{\max}\,, \quad (9)$$

where $\mathbf{I_N}$ denotes an identity matrix of size $N \times N$ and $\boldsymbol{d}_{\max}$ is the vector of demand upper estimates.

Reference [22] covers the analytical details of the networked policy operation.

III. Optimization Process

The analyzed policy needs to be adapted to a given topology and external factors, in particular the demand. In this paper, the perspectives of using GAs for that purpose are explored. The adaptation process concentrates on the selection of TILs, which the nodes will try to maintain in the course of goods reflow in the network. The multidimensional search space imposes application of a numerical approach to find the optimal TIL vector. The variables on which the network state depends are evaluated through simulations. GA is employed to steer the computations towards the optimal solution. Owing to the continuous search space in the discussed inventory control problem (TILs can assume any value in a given interval), the application of continuous-domain GAs is examined [23]. Since the candidate solutions need not be represented in a binary form, typical for GA applications, in the case analyzed here, it is easier to relate the results directly to the problem variables and speed up computations.

A. Fitness Function

The fitness function allows one to determine how closely a given individual conforms to the problem objectives. It takes a candidate solution as an input argument and returns a number indicating the importance of this individual in the population. One cannot obtain the optimal solution *a priori* based solely on the fitness function equation. This function serves the purpose of comparing the individuals in a particular population and judging which one is better than another. Once the evolution terminates the best candidate solution is selected.

In the considered problem, the objective of the optimization process is to reduce the goods holding costs in the network while maintaining high customer satisfaction. The following fitness function has been chosen to quantify this objective

$$fitness(CS, HC, \varepsilon, \sigma) = CS^{\varepsilon}\left(1 - \frac{HC}{HC_0}\right)^{\sigma}, \quad (10)$$

where:

- CS – is the customer satisfaction level related to the quantity of fulfilled external requests, $CS \in [0, 1]$,
- HC_0 – denotes the fixed initial holding cost established from (9),
- HC – is the holding cost obtained for a given vector of TILs,
- ε – is a coefficient that allows one to numerically emphasize the priority of cost reduction,
- σ – is a coefficient stressing the importance of customer satisfaction.

B. Selection

The selection probability for the recombination purposes is calculated for each individual in the population. It is related to the obtained fitness function value calculated according to (10). The selection process is realized using one of the classical methods – stochastic universal sampling (SUS). Unlike the majority of fundamental methods, e.g., roulette wheel selection, SUS divides a given population into pairs using multiple points. In the considered case, two random selectors in each iteration will determine the pair for the next population. The applied approach allows one to reduce the time of executing the selection operation twice with respect to the methods based on only one selector as the pair of individuals (parents) is chosen in a single iteration. Fig. 2 visualizes the selection operation incorporating the SUS technique. The uniformly distributed random points for selection S_1 and S_2 equal 32% and 83%, respectively.

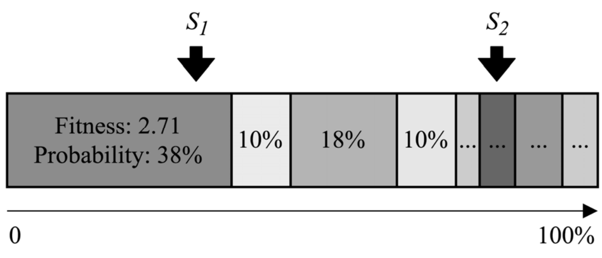

Fig. 2. Stochastic universal sampling.

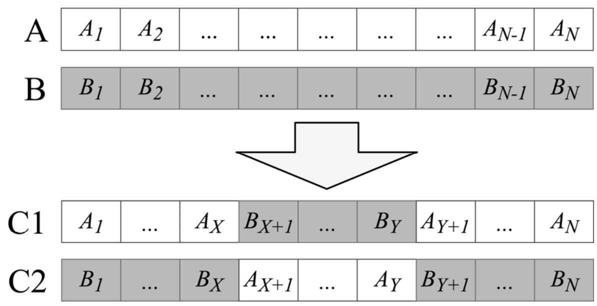

Fig. 3. Multi-point crossover operation.

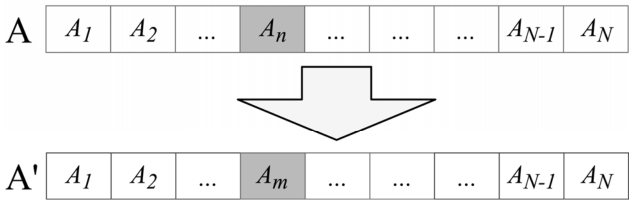

Fig. 4. Uniform mutation operation.

C. Crossover

Recombination is the algorithm step in which each pair of the candidate solutions (parents) creates two new children. As in a biological process, the children inherit traits from their parents. Similarly, in the implemented GA, the TILs in the newly created vectors inherit the traits from the source vectors. In the approach taken in this work, the crossover operation is realized by a multi-point method with two split points. For each pair, two random split points X and Y are determined from the range [0, N]. The split points should be different (X ≠ Y) and are sorted in an ascending order. Once the split points have been established, the crossing operation is performed on the candidate solutions from each pair. Fig. 3 illustrates the crossover operation for individuals A and B using two split points X and Y, where X < Y. As a result, two new individuals C1 and C2 are created.

D. Mutation

The last step of the GA execution as well as the entire evolution process is related to the phenomenon of mutation. This step involves a random gene modification. In the considered continuous-domain problem, the gene modification, i.e., the change of a single element of the TIL vector, can be set only within the boundaries of the search space. Fig. 4 shows the mutation of candidate solution A in which one gene is altered. In biology, mutations occur relatively infrequently. It is assumed here that the mutation probability does not exceed 1–2%.

IV. Numerical Tests

The properties of considered logistic system and performance of GA are evaluated numerically. The optimization process of adjusting the policy parameters to the given logistic topology is realized using the continuous-domain GA described in section III. In order to support numerical research, a simulation program in the Java language was implemented. It enables one to create logistic topologies, satisfying the connectivity and direction assumptions, and to perform goods distribution simulations.

Fig. 5 depicts the structure of logistic network under consideration. There are two external sources (1–2) and three controlled nodes (3–5). The pair of attributes above the connection arrows denote the supply contribution and lead-time delay, respectively. In the considered example, node 3 orders 40% of the required goods from node 1 and their delivery takes 2 periods. The goods distribution process is analyzed with two different types of external demand imposed on the network: one based on gamma distribution and another generated using Poisson distribution. Although for illustrative purposes a non-sophisticated topology has been selected, with the granularity of 1 unit, the full search requires exploring the space of over 10^8 combinations.

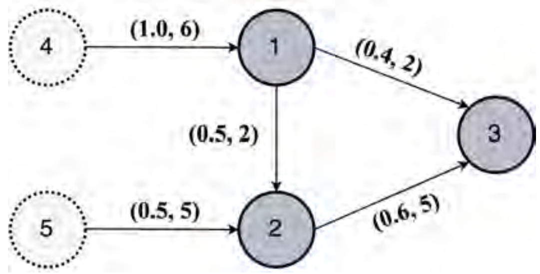

Fig. 5. Network topology.

For GA, the following parameters are assumed:

- the population comprises ten individuals,
- the mutation probability equals 2%,
- the optimization priority coefficients equal ε = 40 and σ = 40, respectively.

The priority coefficients are chosen so that a significant holding cost reduction is obtained while maintaining near full customer satisfaction. The simulation lasts 50 periods and the initial inventory levels are set equal to the target ones, i.e., $\boldsymbol{l}(0) = \boldsymbol{l}^T$. Two stop criteria: the generation limit of 10^4 and the number of generations without fitness values improvements $3 \cdot 10^3$; are enforced.

A. Results for gamma demand

In the first series of simulations, the external demand is generated using gamma distribution, as frequently applied in the study of inventory control problems [23]. Fig. 6 illustrates the demand requests imposed on the nodes in the investigated network. The distribution is parameterized using two coefficients – shape and scale – which are set equal to 5 and 10, respectively.

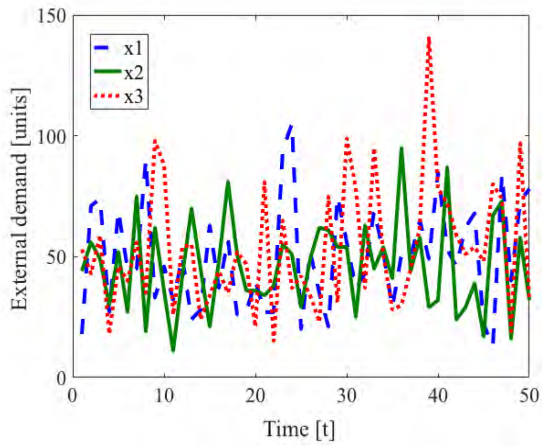

Fig. 6. External demand generated using gamma distribution.

The baseline holding cost for the initial simulation with the external demand fixed to its highest value $\boldsymbol{d}_{\max}$ amounts to $99 \cdot 10^3$. The GA optimization run allows one to keep a full customer satisfaction – 100% fulfilled requests – yet with the costs reduced to $14.5 \cdot 10^3$.

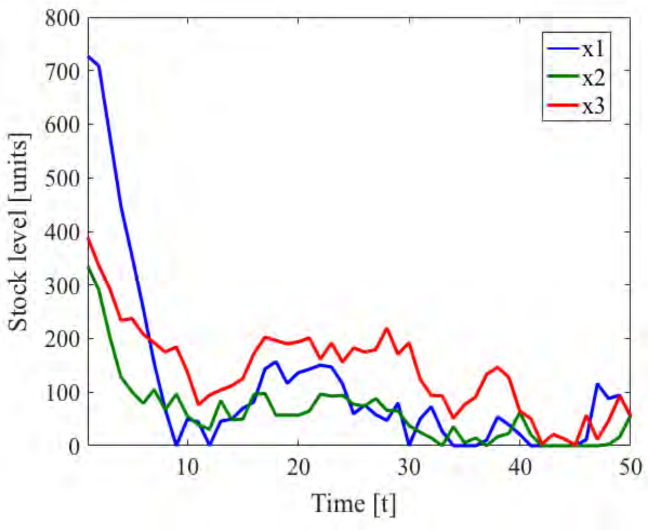

Fig. 7. On-hand stock level after adjusting the networked policy through GA for gamma demand.

Fig. 7 visualizes how the controlled nodes are trying to avoid storing an excessive amount of goods. However, due to the random, *a priori* unknown demand variations (Fig. 6), it is not possible to keep the stock near the zero level all the time.

B. *Results for Poisson demand*

The values obtained from the Poisson distribution are integers, hence they need not be rounded as required in the study of goods reflow. The distribution generator used in the test was parameterized by $\lambda = 10$ and the resulting evolution is sketched in Fig. 8.

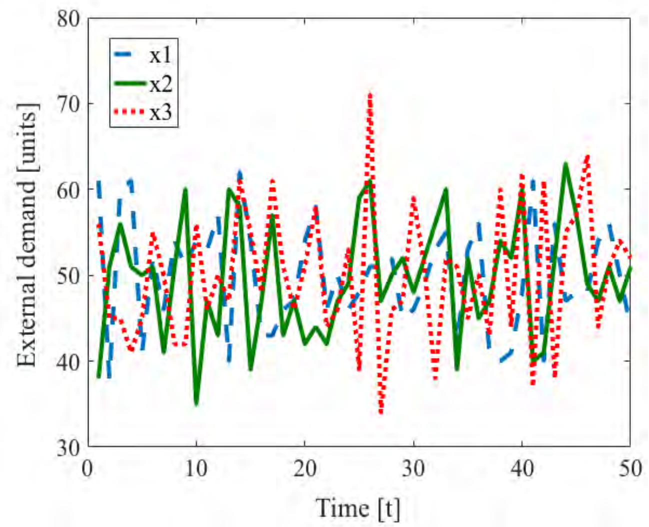

Fig. 8. External demand generated using Poisson distribution.

Similarly, as in the gamma distribution case, the holding cost reduction from $30 \cdot 10^3$ to $4.5 \cdot 10^3$ does not adversely affect the customer satisfaction. Owing to smoother evolution and smaller standard deviation of the assumed Poisson demand, the holding cost reduction via the action of GA is even more profound than in the gamma distribution case. Fig. 9 depicts how the stock reserves decline for the same initial conditions as in the gamma distribution case.

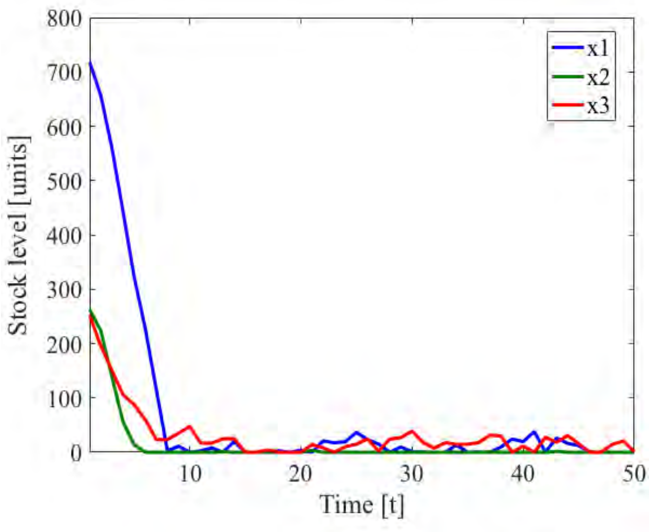

Fig. 9. On-hand stock level after adjusting the networked policy through GA for Poisson demand.

C. *Comments*

The conducted tests confirm that in both cases IV.A and IV.B, GA successfully adjusts the operation of the examined management policy to the time-varying, uncertain demand. Owing to the smaller standard deviation set for the Poisson distribution the holding cost reduction is more substantial. Fig. 10 presents the fitness function changes in the course of the optimization process. The dashed line maps the best solution established using a full search method. Despite the initially slower convergence rate, GA ultimately steers the network towards the optimal state for less variable demand.

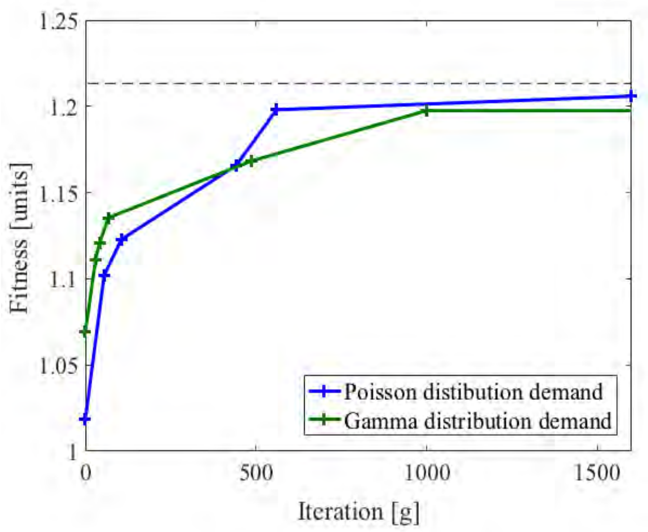

Fig. 10. Progress of the best fitness value improvements.

V. CONCLUSIONS

The paper discusses the application of continuous GAs for optimizing the performance of goods distribution networks with uncertain exogenous demand. The topologies under consideration form a general, mesh-type structure, typically encountered in current logistic systems. The goods distribution process is controlled by a networked inventory policy deployed in a centralized way. Since the external demands are not known *a priori* at the instant of taking the stock replenishment decisions, the policy is adjusted to the given topology and demand type using continuous-domain GA. The implemented GA adapts the target inventory level so that a propitious balance between the holding cost reduction and high customer satisfaction is obtained. The numerical studies, conducted for different network topologies, GA coefficients, and demand distributions, demonstrate the effectiveness of both the considered policy and GAs as tools for artificial intelligence based optimization of modern logistic networks.

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