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Collaborative Bullwhip Effect-Oriented Bi-Objective Optimization for Inference-Based Weighted Moving Average Forecasting in Decentralized Supply Chain

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ABSTRACT

Downstream demand inference (DDI) emerged in the supply chain theory, allowing an upstream actor to infer the demand occurring at his formal downstream actor without need of information sharing. Literature showed that simultaneously minimizing the average inventory level and the bullwhip effect isn't possible. In this paper, the authors show that demand inference is not only possible between direct supply chain links, but also at any downstream level. The authors propose a bi-objective approach to reduce both performance indicators by adopting the genetic algorithm. Simulation results show that bullwhip effect can be reduced highly if specific configurations are selected from the Pareto frontier. Numerical results show that demand's time-series structure, lead-times, holding and shortage costs, don't affect the behaviour of the bullwhip effect indicator. Moreover, the sensitivity analysis show that the optimization approach is robust when faced to varied initializations. Finally, the authors conclude the paper with managerial implications in multi-level supply chains.

KEYWORDS

Bullwhip Effect, Downstream Demand Inference, Genetic Algorithm, Multi-Objective Optimization, Supply Chain Management, Weighted Moving Average Method

1. INTRODUCTION

The supply chain management is increasingly including both theoretical methods and practical recommendations in order to draw more benefits for all supply chain links (Min et al., 2019). Nowadays, a strong tendency to analyze the sustainable performance of supply chains has taken place in the fields of research and industry. While it is not always evident to derive continuous supply chain savings, the directive line in the supply chain management is often the proposal of adapted strategies and techniques that may contribute to supply chain sustainability, such as efficiency-based, innovation-based, or closed-loop strategies (Khan et al., 2022a).

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While the benefits of information sharing policies and systems' integration in the supply chain field such as supply resilience and sustainability are well-known (Khan et al., 2022b), there is a lack of study of how practitioners may achieve higher global performance without complete integration and critical information sharing. Indeed, privacy policies are continuously persisting in many industries. As it was reported in some papers, financial constraints, lack of information systems' compatibility, lack of trust, unwilling of sharing risks and rewards, and information protection laws in different countries, are always leading to sub-optimal solutions which affect the whole supply chain's performance (Cetindamar et al., 2005; Cai et al., 2010). In this context, collaborative forecasting is one of the most distinguished organisational tools that allow performance improvements such as sustainability improvement (Shoukohyar & Seddigh, 2020). Collaborative forecasting refers to the situation where supply chain actors collaborate, either by coordinating forecasting methods or sharing forecast information, in order to achieve higher supply chain's performance. Many authors discussed the impacts of collaborative forecasting on different supply chain industries such as the renewable energy sector (Nam et al., 2020), the defense sector (Kim et al., 2015) or the food sector (Eksoz et al., 2014).

One of the most recent collaborative forecasting strategies is called Downstream Demand Inference (DDI). DDI emerged in the supply chain theory in order to better control the forecasting processes in decentralized supply chains, where demand information is not shared. It proposes balanced solutions for actors who specifically don't want to dislock their strategic demand information. DDI refers to a collaborative forecasting strategy mainly between two supply chain links: an upstream actor and a downstream actor receiving the demand of a customer. Some works already provided an initial vision on this coordination strategy (Ali and Boylan, 2012; Ali et al., 2017). More specifically, the demand inference refers to the mathematical deduction of the customer's demand arriving at the downstream level, based only on the downstream orders' process arriving at the upstream level. The mathematical deduction supposes that the propagation of the demand across the supply chain is unique, which is true under some known assumptions. The works of Ali and Boylan (2011; 2012) showed that DDI is not possible with Single Exponential Smoothing (SES) or Minimum Mean Squared Error (MMSE) forecasting methods. Next, the papers of Ali and Boylan (2011) and Tliche et al. (2019; 2020) showed that the adoption of either Simple Moving Average (SMA) or Weighted Moving Average (WMA) forecasting methods at the downstream level, insures unique demand propagation at the upstream level. This leads to the following conclusion: either with SMA or WMA, for a well-known orders' process at the upstream actor, there exists one unique demand process arriving at the downstream actor. Consequently, it is possible for an upstream actor to estimate and reconstruct the demand process arriving at his formal downstream actor without need of demand information sharing. This research has opened the door to promising new directions on which the authors have aligned.

In the first case, where the downstream actor is adopting the SMA method, DDI strategy proved its efficiency to provide savings in upstream average inventory level and bullwhip effect, when compared to the No Information Sharing (NIS) strategy, under the assumption of Auto-Regressive demand of order 1 (AR(1)) (Ali et al., 2017). In the second case, and in a first attempt of investigation, the weighting vector of the WMA method was determined according to the minimization of the upstream actor's average inventory level (Tliche et al., 2020). The non-equal weightings enhanced the local performance indicator, i.e., the upstream average inventory level, but negatively affected the bullwhip effect, thus deteriorating the global supply chain's performance indicator.

The purpose of this paper is theoretical in the sense that the authors are investigating a new and an uncommon situation. In the knowledge of the authors, there is no literature studying how WMA configuration can reduce bullwhip effect in a context of a DDI strategy. The enhancement of demand processes' understanding along the supply chain and the improvement of forecasting accuracy without violating the confidentiality of demand data, can smooth out high demand alterations over time, avoid supply disruption and ensure a better performance of supply chains' sustainability as the bullwhip effect is affecting the whole supply chain. The best example which highlighted these different aspects of performance when supply chains are decentralised, such as for example the perishable food supply chain (Khan & Ponce, 2021), is certainly the recent Covid-19 crisis.

This work is therefore a natural continuation of previous works in the field of collaborative forecasting in supply chains, thus building on the introduction of the WMA forecasting method in the context of a DDI strategy. The novelties of this research paper are as follows. First, the authors show that it isn't only possible to infer the demand process arriving at his formal downstream actor, but it is also possible to infer the demand at any downstream level in a serial multi-level supply chain, under some assumptions. Second, as the SMA method is a particular case of the WMA method where the ponderations (or weights) allocated to historical observations are all equal, the second contribution is the investigation of the WMA method where forecasting ponderations are unequal. In order to further mitigate the amplification of the bullwhip effect while keeping upstream inventory levels low, a bi-objective orientation was envisaged in order to take into account both key performance indicators. The optimization process allows obtaining non-dominated solutions, thus forming the Pareto border. Compared to one solution, providing a set of Pareto-solutions is more interesting in terms of flexibility and managers' orientations (Trisna et al., 2016). This motivation is justified by the global nature of the bullwhip effect which affects all the supply chain links, when compared to a local inventory-oriented mono-objective optimization. Third, the authors modeled the relationship between the two studied performance metrics which proved to be complex in view of the polynomial's degree of the most appropriate mathematical model. This model captures the relationship in a mathematical form, thus allowing supply chain actors to estimate bullwhip effect improvement in function of average inventory level variation. Fourth, the authors investigated the reliability of the simulation results obtained from the proposed methodology by examining the robustness according to some key supply parameters and algorithm's initialization. They showed that the presented DDI approach is unsensitive to the demand's time-series structure, to the algorithm's initialization and more important, robust in stressful situations where lead-times, holding and shortage costs may vary. The authors finally provided a summary scheme of how this approach can be practically implemented by decision-makers in serial multi-level supply chains.

The main objective of this study is to show that the DDI approach hasn't yet revealed its full potential to improve supply chain performance, especially under causal invertible Auto-Regressive Moving Average (ARMA(p,q)) demands, where p presents the order of the autoregressive demand and q presents the order of the moving average demand (Shumway and Stoffer, 2017). Indeed, the authors show in this study that bi-objective optimisation integrated to collaborative forecasting processes can be useful in improving some key supply chain performance indicators, even in stressful situations. Table 1 presents the main contributions of this research paper as well as some of the recent related papers.

Table 1. Contributions of recent literature

Work	Demand model	Forecasting method	Optimization method	Main contributions
This paper	Causal invertible ARMA(p,q)	WMA	Bi-objective genetic algorithm	- Feasibility of the DDI strategy at any downstream level under the assumption of causality and invertibility - Considerable improvement of bullwhip effect when compared to DDI's literature - Modeling the relationship between average inventory level variation and bullwhip effect - Robustness of the approach to demand time-series structure, supply parameters, and algorithm initialization.
Tliche et al. (2020)	Causal invertible ARMA(p,q)	WMA	Mono-objective Newton method	- Integration of the optimization in the forecasting process - Establishment of the mathematical expressions of the mean squared error, the average inventory and the bullwhip effect with WMA/Newton method under ARMA demands - Improvement of forecasting mean squared error and average inventory level when compared to no collaboration strategy at the expense of bullwhip effect - The performance indicators depend on supply and time-series parameters
Tliche et al. (2019)	Causal invertible ARMA(p,q)	SMA		- Generalization of the DDI feasibility to causal invertible ARMA demands - Establishment of the mathematical expressions of the mean squared error, the average inventory and the bullwhip effect with SMA method under ARMA demands - The performance indicators depend on supply and time-series parameters
Ali et al. (2017)	AR(1)	SMA		- Establishment of the mathematical expressions of the mean squared error with SMA method under AR(1) demands - Mean squared error and inventory costs depend on AR(1) time-series autoregressive coefficient
Ali and Boylan (2012)	ARMA(p,q)	SES and SMA		- DDI isn't possible with SES forecasting method - DDI is feasible with SMA forecasting method.
Ali and Boylan (2011)	ARMA(p,q)	MMSE		- Establishment of the DDI feasibility principles - DDI isn't possible with MMSE forecasting method - Information sharing is more valuable in terms of inventory than DDI strategy

Table 1 continued on next page

Table 1 continued

Work	Demand model	Forecasting method	Optimization method	Main contributions
Hosoda et al. (2008)	AR(1)	MMSE		- Estimation of the standard deviation of predicted errors under information sharing strategy - Information sharing is more valuable in terms of standard deviation of predicted errors
Hosoda and Disney (2006)	AR(1)	MMSE		- Establishment of the mathematical expressions of the bullwhip effect under AR(1) demand - Orders received by the upstream actor contains information about demand received by the downstream actor under AR(1) demands
Gilbert (2005)	ARMA(p,q)	MMSE		- Establishment of the bullwhip effect under AR(1) model - Establishment of the ARIMA inventory models
Zhang (2004)	ARMA(p,q)	MMSE		- Orders received by the upstream actor contains information about demand received by the downstream actor under ARMA demands - Establishment of the ARMA-in-ARMA principle

The rest of the paper is organized as follows. Section 2 is devoted to the literature review and research planning. Section 3 presents the supply chain models and the forecasting optimization problem formulated for this research. In section 4, the authors provide the adopted optimization methodology while the simulation results, the analyses and the managerial implications are provided in section 5. Finally in section 6, the authors resume the key features, the merits and the implications, as well as the future directions.

2. LITERATURE REVIEW AND RESEARCH PLANNING

This section is devoted to the literature review and the plan of the research. The literature review is focusing on the bullwhip effect as it presents a persistent harmful effect that continuously affects the entire supply chain, in an era where globalization is more and more generalized and where sustainability's issues are more and more discussed.

2.1 Bullwhip Effect: A Persistent Harmful Effect

Bullwhip effect is a phenomenon that has been known for a long time and which persists to this day. Lee et al. (1997) illustrated two real-life examples of the bullwhip effect. While examining sales of the Pampers product, executives at Procter and Gamble found that sales in retail stores fluctuated, but the variability wasn't excessive. However, while reviewing distributor orders, managers were surprised by the high degree of variability. Moreover, when these managers looked at the company's orders for raw materials from their suppliers, they found that the variabilities were even greater. On the face of it, the variabilities are meaningless. While customers, babies in this case, were consuming diapers at a steady pace, the demand's variabilities in the supply chain were amplified as they moved up within the supply chain. Similarly, when Hewlett-Packard managers examined sales of one of their printers at a major retailer, they found that there were, as expected, some fluctuations over time. When these managers reviewed the reseller's orders, they observed much greater oscillations. Another more obvious example of this phenomenon is illustrated by the famous "beer game" (Coppini et al., 2010). In the game, actors play the roles of customers, retailers, manufacturers and suppliers of a certain beer's brand. Because of the lack of communication, actors must take decisions based only on orders from the next downstream actor. The ordering shapes shared a common and recurring phenomenon. The variability in demand of an upstream actor is always greater than that of the downstream actor, a simple but powerful illustration of the bullwhip effect. This amplified demand variability, or uncertainty, is generally attributed to the irrational decision making of the actors (Ellram, 2010; Kumar et al., 2013). The bullwhip effect is then presented by the upstream distortion of the demand information flows all along the supply chain. This distortion was commonly represented by the ratio of the upstream demand's variability to the downstream demand's variability (Michna et al., 2020).

A very large number of researchers studied this phenomenon and provided different solutions to mitigate this harmful effect (Chang et al., 2018; Keshari et al., 2018; Bayraktar et al., 2020; Nguyen et al., 2021). Most of the studies involve quantitative analyses with time-series models, simulations and empirical studies, develop structural equations for different scenarios, and use linear or non-linear optimization methods for problem solving. Bullwhip effect generally require high correction costs that can be mitigated through better involvement and collaboration between partners (Bhattacharya and Bandyopadhyay, 2011). For example, de Almeida et al. (2015) identified a list of the main approaches to mitigate the bullwhip effect. These are collaborative approaches such as information sharing policies, improved forecasting methods, replenishment policies, and reduced delivery time. The authors stressed the importance of trust, transparency of information, credibility, flexibility and knowledge sharing among actors.

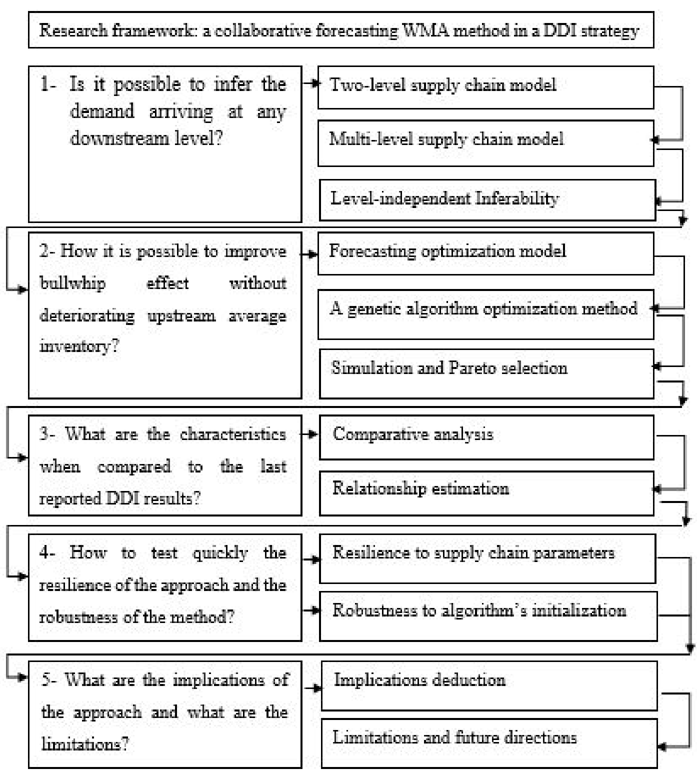
While time-series models have been widely introduced in the supply chain field, and more specifically to investigate information sharing benefits (Tai et al., 2019; Wesonga et al., 2014), the bullwhip effect still persists because of many organisational and behavioral factors (Wu et al., 2021; Yang et al., 2021; Verma et al., 2022). Multi-objective optimisation presents one of the most appropriate solutions that can be considered. It often concerns multiple design objectives under complex, linear or nonlinear constraints. Different objectives often conflict each other, sometimes there are no truly optimal solutions, and compromises are often necessary. In addition to this complexity, a design problem is subject to various design constraints, limited by the design codes or standards, the material properties, and the choice of available resources and costs (Jafarian et al., 2020). Even for mono-objective problems, the overall optimization isn't easy to achieve, if the design functions are highly non-linear.

In operations management, heuristic and metaheuristic methods are very powerful to handle this type of optimization (Wang et al., 2011; Yeh and Chuang, 2011; Yang, 2022). One of the most effective and popular algorithms in computer science and operations research, is the Genetic Algorithm (GA). Many researchers in the supply chain field employed the GA for the resolution of different problems (Diabat and Deskoores, 2016; Jiang et al., 2016; Hiassat et al., 2017; Nakhjirkan et al., 2019). GA refers to a metaheuristic inspired by the process of natural selection that belongs to the larger class of Evolutionary Algorithms (EAs). GAs are commonly used to generate high-quality solutions to multi-objective optimization and research problems by relying on bio-inspired operators such as mutation, crossover and selection. These operators are presented in more details in section 4.

2.2 Research Planning

As this research specifically concerns the DDI strategy in supply chains, the authors briefly resume the last main findings of this approach. DDI is a strategy that allows an upstream actor to mathematically infer the demand arriving at his formal downstream actor. Ali et al. (2017) showed that DDI strategy with SMA method allows improvements of Mean Squared Error (MSE) and inventory costs under AR(1) demand model when compared to the NIS strategy. Then, Tliche et al. (2019) generalized these results to situations of ARMA(p,q) demands, by incorporating the bullwhip effect, in addition to the two first performance indicators. Next, Tliche et al. (2020) introduced the WMA method in the context of the DDI strategy. They showed that the determination of the WMA weights through an inventory-oriented Newton's mono-objective optimization allows considerable improvement of the upstream average inventory level at the expense of the bullwhip effect, when compared to SMA method. Building on these findings, the authors of this paper found it a promising avenue for improvement which directly affects the sustainability dimension as the bullwhip effect is a long-lasting effect that affects the whole supply chain from the retailer to the raw material supplier. The main research question is then: Is it possible to improve bullwhip effect without deteriorating upstream average inventory, in a context of a DDI strategy with WMA forecasting method? Based on this research question, some underlying issues arise. Is it possible to infer the demand arriving at any downstream level? If it is possible, then how to do it? Which method can easily be adopted? What are the characteristics when compared to the last reported DDI results? How to test quickly the resilience of the approach and the robustness of the method before real-life implementation or industry validation? What are the implications of the approach and what are the limitations? In order to answer these issues, we planned the following framework presented in Figure 1.

Figure 1. Research framework



3. SUPPLY CHAIN MODEL AND BI-OBJECTIVE FORECASTING PROBLEM

In this section, the authors first recall the basic two-level supply chain derived from the literature. Then, they generalize the approach to the case of multi-level supply chain showing that demand's inferability isn't restricted to the direct downstream link. Finally, the authors formalize the forecasting optimization problem.

3.1 Two-Level Supply Chain Model

The authors first consider a two-level supply chain where an upstream actor receives orders from a downstream actor. The downstream actor's order is placed after the receipt of a final customer's demand, and after checking his current inventory level. The replenishment policy is thus assumed to follow a periodic system and both actors are assumed to adopt an Order-Up-To inventory policy that minimizes the total costs over infinite time horizon (Caldentey et al., 2022). Let D_t be the demand quantity of the customer over the period t and let Y_t be the orders quantity of the downstream actor at the end of time period t. Once the orders are received, the upstream actor prepares and ships the required quantity after the lead-time period L. Consequently, the downstream actor receives the quantity Y_t at time period $t+L+1$. The unit inventory holding and shortage costs are variable and denoted respectively by h and s.

Let D_t be a causal invertible $ARMA\left(p,q\right)$ demand process at the downstream actor (Shumway and Stoffer, 2017). This process is expressed at period t by equation (1) as follows:

$$D_t = c + \sum_{j=1}^{p}\phi_j D_{t-j} + \xi_t + \sum_{j=1}^{q}\theta_j \xi_{t-j} \tag{1}$$

where:

- $c \geq 0$ is the unconditional mean of the demand process.
- $\phi_j, j \in \left\{1,\ldots,p\right\}$ are the autoregressive coefficients of the demand process.
- $\theta_j, j \in \left\{1,\ldots,q\right\}$ are the moving average coefficients of the demand process.
- $\xi_t \rightarrow N\left(0,\sigma_\xi^2\right), t \in \mathbb{N}^+$ are the errors terms of the demand process, independently and identically distributed according to the normal distribution.

Assuming the decentralized criteria of the two-level supply chain, the demand at the downstream actor is unknown to the upstream actor as he holds only orders' historical information. In such context, DDI strategy allows the upstream actor to infer the customer's demand without having to go through formal information sharing. It was already shown that if the downstream actor uses the WMA method to forecast the customer's demand, the orders process at the upstream actor would also follow an $ARMA\left(p,q\right)$ process with some differences (Tliche et al., 2020). Let first recall this statement.

At the downstream level, the WMA forecasting method affects non-equal weights to the most recent N demand observations. At period $t+1$, the forecast is expressed by equation (2) as follows:

$$f_{t+1} = \sum_{i=1}^{N} x_i D_{t+1-i} \tag{2}$$

where x_i is the weight associated to the observed demand occurring at time $t+1-i$, and verifying the set of constraints:

$$\left(C\right):\begin{cases} \sum_{i=1}^{N} x_i = 1 \\ x_i \geq 0 \forall i \in \left\{1,\ldots,N\right\} \end{cases}$$

Let Y_t be the orders process arriving at the upstream actor at period t. This process is expressed by equation (3) as follows:

$$Y_t = c + \sum_{j=1}^{p} \phi_j Y_{t-j} + \tilde{\xi}_t + \sum_{j=1}^{q} \theta_j \tilde{\xi}_{t-j} \tag{3}$$

where:

- $c \geq 0$ is the unconditional mean of the orders process.
- $\phi_j, j \in \left\{1,\ldots,p\right\}$ are the autoregressive coefficients of the orders process.
- $\theta_j, j \in \left\{1,\ldots,q\right\}$ are the moving average coefficients of the orders process.
- $\tilde{\xi}_t \rightarrow N\left(0,\left[L^2\left(x_1^2 + x_N^2 + \sum_{i=1}^{N-1}\left(x_{i+1} - x_i\right)^2\right) + 2Lx_1 + 1\right]\sigma_\xi^2\right), t \in \mathbb{N}^+$ are the errors terms of the orders process, independently and identically distributed according to the normal distribution.

Thus, the upstream propagation of the demand along the supply chain keeps the same autoregressive and moving average coefficients ϕ_j and θ_j. The difference lies on the residual structure of the process. Indeed, the orders' error terms $\tilde{\xi}_t$ are a linear function of the demand's error terms, expressed by $\tilde{\xi}_t = L\left(\sum_{i=1}^{N} x_i \left(\xi_{t-i+1} - \xi_{t-i}\right)\right) + \xi_t$. Moreover, the variance of the error term is amplified by a strictly positive real expressed by:

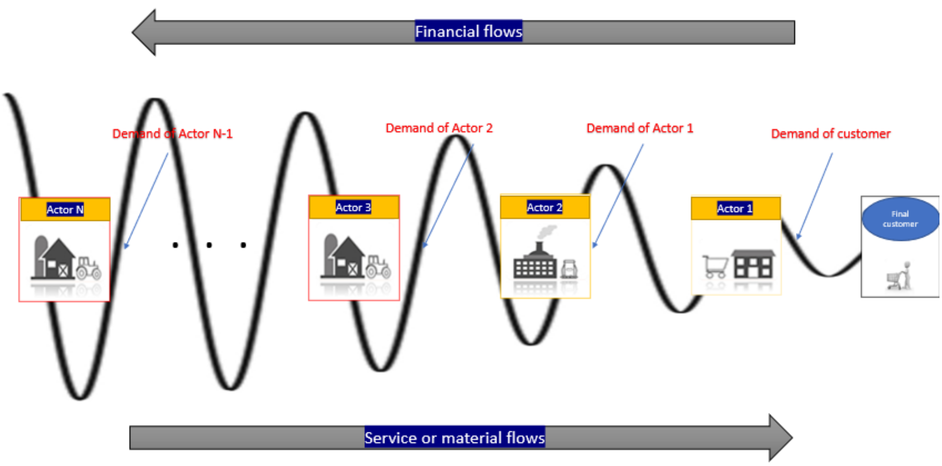
$$\beta = L^2\left(x_1^2 + x_N^2 + \sum_{i=1}^{N-1}\left(x_{i+1} - x_i\right)^2\right) + 2Lx_1 + 1$$

Considering such transformations, the propagation is always unique. The upstream actor is consequently able to infer the demand arriving at the downstream level without need of information sharing mechanisms. The downstream actor is then no longer invited to share his demand information and the issue of disclosing information is over.

3.2 Multi-Level Supply Chain Model

Let consider a serial multi-level supply chain composed of n actors where WMA forecasting method is adopted by all links, as shown in Figure 2.

Figure 2. Demand propagation in a serial multi-level supply chain



The generalized mathematical model in this sub-section is a natural inductive deduction from the two-level supply chain model, as it can follows a serial two-by-two reasoning.

3.2.1 Proposition: Level-Independent Inferability

If the demand of a final customer is:

$$D_t = Y_{0,t} = c + \sum_{j=1}^{p} \phi_j D_{t-j} + \xi_t + \sum_{j=1}^{q} \theta_j \xi_{t-j}$$

with $\xi_t \to N\left(0, \sigma_\xi^2\right)$.

Then:

Orders of Actor 1: $Y_{1,t} = c + \sum_{j=1}^{p} \phi_j Y_{1,t-j} + \tilde{\xi}_{1,t} + \sum_{j=1}^{q} \theta_j \tilde{\xi}_{1,t-j}$ with $\tilde{\xi}_{1,t} \to N\left(0, \beta\ \sigma_\xi^2\right)$

Orders of Actor 2: $Y_{2,t} = c + \sum_{j=1}^{p} \phi_j Y_{2,t-j} + \tilde{\xi}_{2,t} + \sum_{j=1}^{q} \theta_j \tilde{\xi}_{2,t-j}$ with $\tilde{\xi}_{2,t} \to N\left(0, \beta^2\ \sigma_\xi^2\right)$

Orders of Actor 3: $Y_{3,t} = c + \sum_{j=1}^{p} \phi_j Y_{3t-j} + \tilde{\xi}_{3,t} + \sum_{j=1}^{q} \theta_j \tilde{\xi}_{3,t-j}$ with $\tilde{\xi}_{3,t} \to N\left(0, \beta^3\ \sigma_\xi^2\right)$

$\vdots$

Orders of Actor $n-1$: $Y_{n-1,t} = c + \sum_{j=1}^{p} \phi_j Y_{n-1,t-j} + \tilde{\xi}_{n-1,t} + \sum_{j=1}^{q} \theta_j \tilde{\xi}_{n-1,t-j}$ with $\tilde{\xi}_{n-1,t} \rightarrow N\left(0, \beta^{n-1}\ \sigma_{\xi}^2\right)$

Hence, when moving up a level in the supply chain, the error term is a linear function of the first downstream error term:

$$\tilde{\xi}_t = L\left(\sum_{i=1}^{N} x_i \left(\xi_{t-i+1} - \xi_{t-i}\right)\right) + \xi_t$$

where the variability is amplified by:

$$\beta = L^2\left(x_1^2 + x_N^2 + \sum_{i=1}^{N-1}\left(x_{i+1} - x_i\right)^2\right) + 2Lx_1 + 1$$

This model implies that the actor n is able to infer the demand arriving at any downstream level $j, j = 1, \ldots, n-1$.

For illustration, if the demand structure at actor 6 is following an $ARMA(4,2)$ model, then the demand structure at the actor 3 is following an $ARMA(4,2)$ model with the same autoregressive and moving average parameters, but different error's structure. Let's note: If the demand arriving at actor 6 (or orders of actor 5) can be expressed by:

$$Y_{5,t} = 50 + \sum_{j=1}^{4} \phi_j Y_{5,t-j} + \xi_{5,t} + \sum_{j=1}^{2} \theta_j \xi_{5,t-j}$$

with $\xi_{5,t} \rightarrow N(0,1)$ then the demand at actor 3 (or orders of actor 2) is expressed by:

$$Y_{2,t} = 50 + \sum_{j=1}^{4} \phi_j Y_{2,t-j} + \tilde{\xi}_t + \sum_{j=1}^{2} \theta_j \tilde{\xi}_{2,t-j}$$

with $\tilde{\xi}_{2,t} \rightarrow N\left(0, \beta^{-3}\right)$. Moreover, the demand of the final customer arriving at actor 1 is expressed by:

$$D_t = Y_{0,t} = 50 + \sum_{j=1}^{4} \phi_j D_{t-j} + \tilde{\xi}_t + \sum_{j=1}^{2} \theta_j \tilde{\xi}_{t-j}$$

with $\tilde{\xi}_t \rightarrow N\left(0, \beta^{-5}\right)$.

This strong capability of inference in the case of a WMA method, at any level of a serial supply chain, first justify the motivation to explore the DDI results when compared to the last reported results (Tliche et al., 2020). Since the root cause of the bullwhip effect starts at the orders of the first level, the authors will first focus on the first two-level supply chain, and then drive the implications for the whole multi-level supply chain.

Of course, to precisely infer the demand at any downstream level of the supply chain, the upstream actor needs to know the values of the data horizon N, the lead-time L and the weighting vector used in the WMA method, i.e., $x_1,\ldots,x_N$, as β is function of these parameters. As argued in the paper of Ali et al. (2017), the partners of a supply chain would collaborate on sharing supply and forecasting parameters rather than sharing critical demand information.

3.3 Bi-Objective Forecasting Problem

If the downstream actor adopts the WMA/Newton method as described in the work of Tliche et al. (2020), two important results are to be taken into account: the first one is the induction of additional inventory savings at the upstream actor; hence, local savings at the upstream level when compared to the situation of a SMA method. However, the second result corresponds to the amplification of the bullwhip effect. This orders' variability involves high uncertainty at the strategic level and may cause irreversible losses for all supply chain actors. In fact, optimizing two conflictive objectives at the same time isn't really possible.

Since the amplification of the bullwhip effect is irreversible when minimizing the upstream average inventory level in a DDI strategy, the upstream actor is able to mitigate this amplification by applying a different optimisation process. This optimization may constitute a preliminary to be integrated into the downstream actor's forecasting process. Under the DDI strategy, while $\tilde{I}_t^{DDI}\left(x\right)$ presents the upstream average inventory level from period $t+1$ to period $t+L+1$, where $x^t=\left(x_1,\ldots,x_N\right)$ is the weighting vector of the most recent N observations, the $BEA^{DDI}\left(x\right)$ metric presents bullwhip effect amplification expressed by the ratio of the bullwhip effect generated by employing WMA method, related to the bullwhip effect generated by employing SMA method. The SMA method is used as a benchmark given that it is the first method, apart from the WMA method, to have ensured the capability of inference. That said, the results of the SMA method will serve as a benchmark for improvement in terms of bullwhip effect. The authors thus define the Bi-Objective Forecasting Problem (BOFP) as follows:

$$\left(BOFP\right):\begin{cases}\min\ \ upstream\ \ average\ \ inventory\ \ level & \left(local\ \ optimization\right)\\ \min\ \ bullwhip\ \ effect\ \ amplification & \left(global\ \ optimization\right)\end{cases}$$

$$\Leftrightarrow\left(BOFP\right):\begin{cases}\min\tilde{I}_t^{DDI}\left(x\right)\\ \min BEA^{DDI}\left(x\right)=\dfrac{BWeffect^{WMA}}{BWeffect^{SMA}}\left(x\right)\\ s.t\begin{cases}\sum_{i=1}^{N}x_i=1\\ x_i\geq 0\ \forall i=1,\ldots,N\\ x^t=\left(x_1,\ldots,x_N\right)\end{cases}\end{cases}$$

$$\Leftrightarrow \left(BOFP\right): \begin{cases} \min \dfrac{c}{2\left(1-\sum_{j=1}^{p}\phi_j\right)} + K\sigma_{\tilde{\xi}}\sqrt{MSE^{DDI}\left(x\right)} \\ \min \dfrac{N^2\left[L^2\left(x_1^2+x_N^2+\sum_{i=1}^{N-1}\left(x_{i+1}-x_i\right)^2\right)+2Lx_1+1\right]}{2L^2+N^2+2NL} \\ s.t. \begin{cases} \sum_{i=1}^{N} x_i = 1 \\ x_i \geq 0 \ \forall i = 1,\ldots,N \\ x^t = \left(x_1,\ldots,x_N\right) \end{cases} \end{cases}$$

where:

$$MSE^{DDI}\left(x\right) = \left(L+1\right)\gamma_0 + 2\sum_{i=1}^{L} i\gamma_{L+1-i} + \left(L+1\right)^2\left[\gamma_0\sum_{i=1}^{N}x_i^{\,2} + 2\sum_{j=1}^{N-1}\left(x_j\sum_{i=j+1}^{N}x_i\gamma_{i-j}\right)\right]$$
$$-2\left(L+1\right)\sum_{i=1}^{L+1}\sum_{j=1}^{N}x_j\gamma_{i+j-1}$$

is the mean squared error over the lead-time period L at weighting configuration x, γ_j is the auto-covariance function of the demand process at time period j, $K = F^{-1}_{N(0,1)}\left(\dfrac{s}{s+h}\right)$ is the reciprocal standard normal distribution at $\dfrac{s}{s+h}$, and $\sigma_{\tilde{\xi}}$ is the standard deviation of the orders' error terms $\tilde{\xi}_t$.

The two non-linear objective functions at the BOFP formulation show the complexity of the matter. While, the first function depends on lead time L and parameter N, weighting vector x, demand time-series structure (c, ϕ_j, γ_j), standard deviation of orders' errors $\left(\sigma_{\tilde{\xi}}\right)$, holding and shortage costs $\left(h,s\right)$, the second function depends only on weighting vector x, lead time L and parameter N. The conflictive character of these two functions will illustrate be illustrated based on the Pareto borders discussed in Section 5.

We also note here that the prediction capability is enhanced when the average inventory level is improved. Indeed, we can see from BOFP formulation that the forecasting MSE can be expressed by:

$$MSE^{DDI}\left(x\right) = \left(\frac{\tilde{I}_t^{DDI}\left(x\right) - \dfrac{c}{2\left(1-\sum_{j=1}^{p}\phi_j\right)}}{K\sigma_{\tilde{\xi}}}\right)^2$$

which is a strictly positive non-linear function of the average inventory level. Consequently, the reduction of the average inventory level corresponds to a substantial reduction in terms of forecasting error which enables higher forecasting capabilities.

4. OPTIMIZATION METHODOLOGY

In this section, we address the optimization methodology adopted in this research by presenting the well-known multi-objective optimization as well as the adopted evolutionary genetic algorithm and its main advantages.

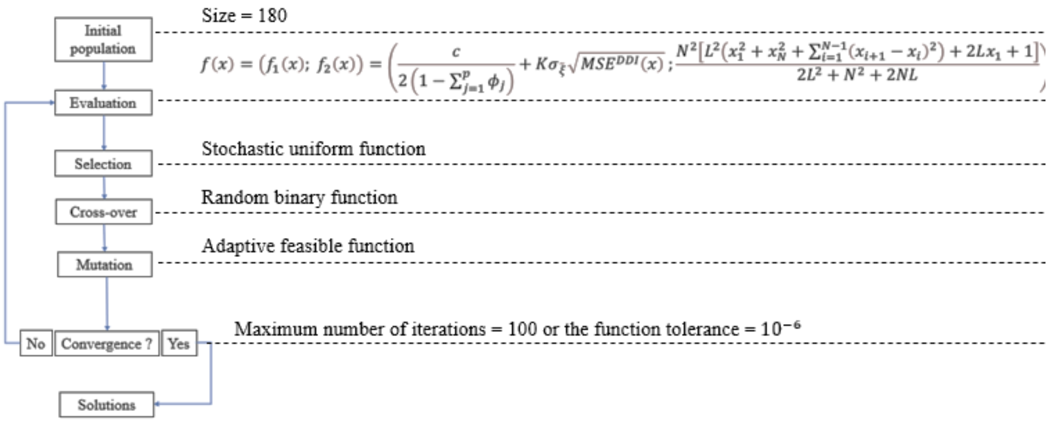
4.1 Multi-Objective Optimisation

Multi-objective optimization is a mathematical branch that allows the optimization (minimization or maximization) of multiple objectives under some defined set of constraints (Kadziński et al., 2017). In this context, instead of a unique best solution, a set of solutions, called “non-dominated”, are derived in order to get a good approximation to the theoretical Pareto front. Evolutionary Computation presents one of the most efficient techniques that respond to multi-objective optimization. In this field, a large set of algorithms allow the resolution of multi-objective problems. The main advantage of the EAs is that they are stochastic and mostly heuristic. Instead of searching the overall space, finding the best solutions in each population and using them to improve newer solutions allow these algorithms to search only promising regions of the search space. These algorithms are sometimes criticized because they don’t lead to similar solutions after several executions, as opposed to deterministic algorithms, which provide same solutions after every execution. However, when the dimension of the problem is high, deterministic algorithms have a much slower speed of execution and risk stopping on locally optimal solutions. The popularity of the EAs made their applications common in many research areas. Another advantage of EAs is that they consider optimization problems as black boxes. Users of EAs, as opposed to gradient-based optimisation algorithms, don’t require knowing the shape of search space or the line to follow in order to reach solutions (Deb, 2011).

4.2 An Evolutionary Bi-Objective Genetic Algorithm

One of the best EAs is the GA which mimics the darwinian theory of “Survival of the fittest” in nature (Kumar et al., 2020; Arık et al., 2021). In nature, the most tenacious organisms are more likely to survive, and later, pass on their genes to future generations. The first step is to randomly consider a starting population as solutions that will be evaluated by a fitness function, hence indicating their respective relevancies. Then, an iterative process is performed in order to choose the fittest solutions. In each iteration, the best solutions are selected, stochastically combined and mutated, to produce the next set of generations. Three main components integrate the algorithm: selection, crossover and mutation. The crossover and mutation operators are equipped with several stochastic functions such as weighted sum functions and probabilistic distributions. In this study, the Bi-Objective Genetic Algorithm (BOGA) is detailed in Figure 3.

Figure 3. Adapted Bi-objective genetic algorithm



The evaluation function is a two-component vector of the upstream average inventory level and the bullwhip effect amplification separating WMA to SMA method.

The selection function selects two individuals from the population as the parents of the next generation in terms of their scaled values from the fitness scaling function. Concretely, the identification of each parent is done through a stochastic uniform function, laying out a line where each parent corresponds to a section of the line of length proportional to its expectation.

The crossover function associates two observations, or two parents, to produce a new observation, or a child for the next generation. In this case, the generation is done through a scattered function that creates a random binary vector where one presents the case of selecting the gene from the first parent and zero presents the case of selecting the gene from the second parent.

The mutation function makes small random changes for individuals in the population, which generate genetic diversity and allow the BOGA to seek a larger space. In this case, the constraint-dependant and more specifically, the adaptive feasible function is used as a mutation function. This function randomly generates directions that are adaptive with respect to the last effective or ineffective generation. Besides, a step length characterizes each direction so constraints aren't violated.

The BOGA can quickly reach the region near an optimal Pareto front, when compared to other algorithms. Besides, the BOGA is intrinsically parallel. This parallelism makes possible to explore broad search spaces without the need to exploit a specific heuristic. Thus as discussed, the BOGA doesn't give a solution but a set of optimal solutions that form the Pareto border. Each solution on this border is an acceptable solution for the BOFP, and presents a different configuration of the WMA weighting vector, at the downstream level. The resulting Pareto-optimal solutions are much more interesting than a single solution since they allow flexibility when considering real data and would allow supply managers to exploit their own experiences in choosing the adequate solution. In addition, and in this context, this will enable the authors to choose the solutions that match the expectations, i.e., reducing as much as possible the bullwhip effect while keeping the upstream inventory levels low.

In the next section, the authors present the simulated demands, the simulations' results and interpretations their interpretations, as well as the managerial implications of these results.

5. SIMULATION AND ANALYSES

The multi-objective optimization tool was used on Matlab software, and the authors adapted it to match the defined BOFP. Concretely, the 'gamultiobj' function of the controlled elitist genetic algorithm (Deb, 2011) was exploited for all different problems with regard to the simulated ARMA(p,q) models presented in Table 2. It is important to maintain the diversity (based on the function space) of the population for convergence to an optimal Pareto front. For the first four subsections, the authors fixed the forecasting horizon $N = 12$ and the lead-time $L = 5$. They also fixed the holding cost at $h = 1$ and shortage cost at $s = 2$. The authors defined the bi-objective function (fitness function) on a separate Matlab file and they tested the algorithm using a fixed population size set at 20. The stopping criterion can be defined in many ways. One can use either a given tolerance and/or a fixed number of iterations. The maximum number of iterations was set at 100, and the function tolerance at 10^{-6}. The computing time was at the scale of some minutes on a Windows 7 professional system. For each execution, the BOGA provided 63 solutions which form the Pareto border of each simulated problem.

Table 2. Simulated ARMA demands

Simulated demand	Expression
1	$D_t = 10 + 0,400 D_{t-1} + \xi_t$
2	$D_t = 10 + 0,500 D_{t-1} + \xi_t$
3	$D_t = 10 + 0,600 D_{t-1} + \xi_t$
4	$D_t = 10 + \xi_t + 0,400 \xi_{t-1}$
5	$D_t = 10 + \xi_t + 0,500 \xi_{t-1}$
6	$D_t = 10 + \xi_t + 0,600 \xi_{t-1}$
7	$D_t = 10 + 0,400 D_{t-1} + \xi_t + 0,051 \xi_{t-1}$
8	$D_t = 10 + 0,400 D_{t-1} + \xi_t + 0,100 \xi_{t-1}$
9	$D_t = 10 + 0,400 D_{t-1} + \xi_t + 0,300 \xi_{t-1}$
10	$D_t = 10 + 0,400 D_{t-1} + \xi_t + 0,300 \xi_{t-1} + 0,100 \xi_{t-2}$

Table 2 continued on next page

Table 2 continued

Simulated demand	Expression
11	$D_t = 10 + 0,400 D_{t-1} + \xi_t + 0,300 \xi_{t-1} + 0,150 \xi_{t-2}$
12	$D_t = 10 + 0,400 D_{t-1} + \xi_t + 0,300 \xi_{t-1} + 0,200 \xi_{t-2}$
13	$D_t = 10 + 0,400 D_{t-1} + \xi_t + 0,300 \xi_{t-1} + 0,180 \xi_{t-2} + 0,060 \xi_{t-3} + 0,050 \xi_{t-4}$
14	$D_t = 10 + 0,200 D_{t-1} + 0,150 D_{t-2} + \xi_t + 0,100 \xi_{t-1}$
15	$D_t = 10 + 0,200 D_{t-1} + 0,150 D_{t-2} + 0,120 D_{t-3} + 0,100 D_{t-4} + \xi_t + 0,100 \xi_{t-1}$
16	$D_t = 10 + 0,200 D_{t-1} + 0,150 D_{t-2} + 0,120 D_{t-3}$ $+0,100 D_{t-4} + \xi_t + 0,100 \xi_{t-1} + 0,065 \xi_{t-2}$
17	$D_t = 10 + 0,200 D_{t-1} + 0,150 D_{t-2} + 0,120 D_{t-3} + 0,100 D_{t-4}$ $+\xi_t + 0,100 \xi_{t-1} + 0,065 \xi_{t-2} + 0,060 \xi_{t-3} + 0,051 \xi_{t-4}$
18	
19	$D_t = 10 + 0,200 D_{t-1} - 0,150 D_{t-2} + 0,120 D_{t-3} - 0,100 D_{t-4} + 0,080 D_{t-5}$ $+0,070 D_{t-6} + 0,060 D_{t-7} - 0,051 D_{t-8} + \xi_t + 0,100 \xi_{t-1} + 0,060 \xi_{t-2}$
20	$D_t = 10 + 0,200 D_{t-1} - 0,150 D_{t-2} + 0,120 D_{t-3} - 0,100 D_{t-4} + 0,080 D_{t-5}$ $+0,070 D_{t-6} + 0,060 D_{t-7} - 0,051 D_{t-8} + \xi_t + 0,100 \xi_{t-1}$ $+0,060 \xi_{t-2} + 0,040 \xi_{t-3} + 0,010 \xi_{t-4}$

5.1 Pareto Optimization

The figures in the appendix show the results of the Pareto optimization of twenty BOFP according to their specified simulated demands in Table 2. As discussed, solutions in each figure are defined by their evaluation function $f = \left(\tilde{I}_t^{DDI}\left(x\right); BEA^{DDI}\left(x\right)\right)$ representing independently the two conflictive objective functions of the BOFP. In addition, each solution characterizes a different weighting vector setting x to introduce in the downstream actor forecasting process. With such flexibility, managers are often able to choose which solutions best match their expectations.

First of all, it is clear from the figures at the appendix, that most (three quarters) of the pareto borders present solutions below the red lines. Set at a threshold value of 1, these red lines present the limit of BEA^{DDI} not to be exceeded if the actors in the supply chain want to ensure increased performance in terms of bullwhip effect, when compared to SMA method. Indeed, supply chain managers should consider solutions whose projections along the y-axis are less or equal to 1, and then select a solution from this space to be applied in the downstream forecasting. Second, as the authors are focusing on the mitigation of the bullwhip effect while keeping inventory levels low, they marked solutions with the minimum values of BEA^{DDI} indicator. These solutions are providing the highest improvements when compared to solutions provided by the SMA method. These solutions marked by 4-pointed stars were called "star-solutions". Indeed, the authors can consider for example the star-solution of problem 1 at the first figure of the appendix and analyze the performance results of its setting. The weighting vector identified by the solution $x^* =$ (0.028; 0.072; 0.092; 0.081; 0.102; 0.084; 0.073; 0.108; 0.121; 0.092; 0.075; 0.066) gives unequal importance to past observations and characterizes the evaluation function $f^* = \left(\tilde{I}_t^{DDI} = 11.6552; BEA^{DDI} = 0.7186\right)$. Specifically, as BEA^{DDI} indicator lies between 0 and 1, the more this value approaches 0, the more the bullwhip effect improvement is considerable. This setting corresponds to the maximum reduction of the bullwhip effect amplification, among all the solutions forming the Pareto border and corresponding to problem 1.

5.2 Comparative Study on Mono-Objective and Bi-Objective Optimized Forecasting

For purpose of comparison, the authors present in Table 3 the results of the average inventory levels and the bullwhip effect amplifications according to the adopted forecasting methods. For each problem characterized by its own demand, while the WMA/Newton results are the ones performed by the integration of the mono-objective Newton method into the WMA forecasting (Tliche et al., 2020), the WMA/BOGA* results correspond to the ones performed by the integration of the BOGA into the WMA forecasting, where the weighting vectors are determined by the star-solutions, which minimize the bullwhip effect amplifications among the Pareto frontier.

Table 3. Average inventory level and bullwhip effect amplification according to WMA/Newton and WMA/BOGA*

Demand Model	$\tilde{I}_t^{DDI}$		BEA^{DDI}	
	WMA/Newton	WMA/BOGA*	WMA/Newton	WMA/BOGA*
1	11.4855	11,6552	8.0351	0.7186
2	14.2098	14,3869	8.8732	1,1233
3	18.2922	18,7491	10.2814	0,9949
4	7.4038	7,5061	7.5548	0,6520
5	7.7376	7,8811	7.8568	0,5944
6	8.0942	8,2293	8.1322	0,7465
7	11.7838	11,9200	8.2624	0,8932
8	12.0835	12,3569	8.5025	0,6714
9	13.4401	13,8743	9.5634	0,8538
10	14.1049	14,9002	10.2073	0,6415
11	14.4536	15,0148	10.5797	0,9764
12	14.8132	15,1154	10.9764	1,6828

Table 3 continued on next page

Table 3 continued

Demand Model	$\tilde{I}_t^{DDI}$		BEA^{DDI}	
	WMA/Newton	WMA/BOGA*	WMA/Newton	WMA/BOGA*
13	15.2839	16,0223	11.3773	1,0110
14	10.7887	10,9570	8.0352	0,7555
15	15.6680	16,0364	9.1444	0,9908
16	16.0256	16,1562	9.5308	1,6021
17	16.4813	16,8579	10.2582	1,1342
18	8.3972	8,4774	7.3549	0,6455
19	8.5747	8,6403	7.4530	0,8931
20	8.7030	8,8272	7.5625	0,6441

The simulation results in Table 3 show that a very slight increase in the average inventory level generally corresponds to an important decrease in the bullwhip effect amplification. For example, considering the simulated problem 20, the results of WMA/Newton forecasting method reported a value of BEA^{DDI} equal to 7.5625, and the corresponding percentage decrease in terms of bullwhip effect amplification when adopting the WMA/BOGA* is equal to:

$$\left|\frac{0,6441-7.5625}{7.5625}\right|\times 100 \approx 91.48\%$$

Likewise, the results of WMA/Newton forecasting method reported a value of $\tilde{I}_t^{DDI} = 7.5625$ and the percentage increase in terms of average inventory level is equal to:

$$\left|\frac{8,8272-8.7030}{8.7030}\right|\times 100 \approx 1.42\%$$

The two performance metrics behave conflictedly such as "return" and "risk". It is important for supply chain managers to understand that there is no perfectly optimized solutions and there are always trade-offs to be respected. While it's interesting to investigate the behaviors of these performance metrics, the authors present in Table 4, the percentages gaps separating WMA/Newton to WMA/BOGA. By denoting by DDI* the situation where WMA/BOGA* is used and by DDI the situation where WMA/Newton is used, the performance gaps are computed in percentages in the following manner:

$$BEA^{DDI}\_variation = \left| \frac{BEA^{DDI*} - BEA^{DDI}}{BEA^{DDI}} \right| \times 100$$

and:

$$\tilde{I}_t^{DDI}\_variation = \left| \frac{\tilde{I}_t^{DDI*} - \tilde{I}_t^{DDI}}{\tilde{I}_t^{DDI}} \right| \times 100$$

Table 4. Percentage gaps of average inventory level and bullwhip effect amplification separating WMA/BOGA* to WMA/Newton

Demand Model	$\tilde{I}_t^{DDI}$ variation	BEA^{DDI} variation
1	1.47%	−91.05%
2	1.24%	−87.34%
3	2.49%	−90.32%
4	1.38%	−91.36%
5	1.85%	−92.43%
6	1.66%	−90.82%
7	1.15%	−89.18%
8	2.26%	−92.10%
9	3.23%	−91.07%
10	5.63%	−93.71%
11	3.88%	−90.77%
12	2.04%	−84.66%
13	4.83%	−91.11%
14	1.55%	−90.59%
15	2.35%	−89.16%
16	0.81%	−83.19%
17	2.28%	−88.94%

Table 4 continued on next page

Table 4 continued

Demand Model	$\tilde{I}_t^{DDI}$ variation	BEA^{DDI} variation
18	0.95%	-91.22%
19	0.76%	-88.01%
20	1.42%	-91.48%
Mean	2.16%	-89.92%

Table 4 shows that percentage decrease of bullwhip effect amplification, exceeds far away the percentage increase of upstream average inventory levels. Based on the twenty simulated models, the average reduction in terms of bullwhip effect amplification is nearly 44 times the increase in upstream average inventory levels. This result reflects the strength of BOGA to effectively detect solutions that correspond to an increased overall performance of a slightly less efficient local performance. This further strengthens the possibility of negotiating a collaboration agreement with a downstream actor and proposing joint improvements. In addition, Table 4 suggests a possible relation between the two percentages. If a relation is statistically significant, supply chain managers will be able to predict the bullwhip effect's improvement when moving from a mono-objective solution to a bi-objective star-solution, which provides a solid basis for estimating supply chain's savings.

5.3 Relationship Between Local and Global Performance

Performed under SPSS software, Tables 5, 6, and 7 show the resulting output of the linear regression of the percentage decrease of the bullwhip effect amplification, on the percentage increase of the upstream average inventory level.

Table 5. Linear regression of the percentage decrease of bullwhip effect amplification, on the percentage increase of average inventory level

Model	R	R^2	$R^2_{adjusted}$	Standard error of estimation
1	,446[a]	,199	,154	2,34118183157918

Predictors: (Constant), Increase of average inventory level

Table 6. Analysis of variance of the percentage decrease of bullwhip effect amplification on the percentage increase of average inventory level

Model		Sum of Squared	Ddl	Mean of Squared	F	Sig.
1	Regression of Student	24,474	1	24,474	4,465	,049
		98,660	18	5,481		
	Total	123,134	19			

Table 7. Coefficients of the linear regression of the percentage decrease of bullwhip effect amplification on the percentage increase of average inventory level

Model		Unstandardized coefficients		Standardized coefficients	t	Sig.
		B	Standard Error	Bêta		
1	(Constant)	88,061	1,028		85,691	,000
	Increase of average inventory level	,863	,408	,446	2,113	,049

Dependant variable: Decrease of bullwhip effect amplification

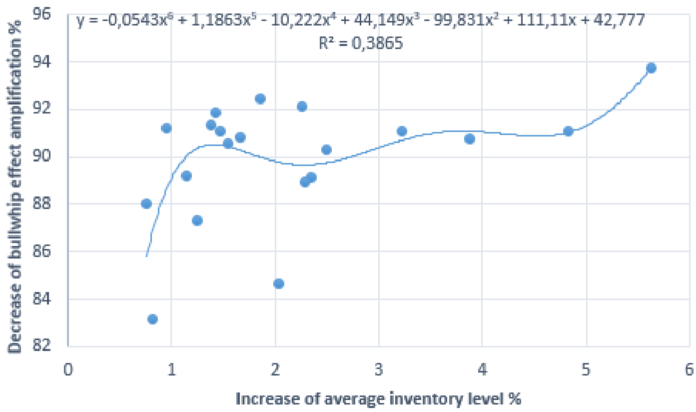
Table 6 displays an F value equal to 4,465, which is significant at a p-value < 0.05. In this case, the authors conclude the significant relationship between the dependent variable (Y = the percentage decrease of the bullwhip effect amplification) to the independent variable (X = percentage increase of the average inventory level). In addition, Table 5 shows an absolute correlation coefficient R of the order of 0.446. This suggests a relationship of a moderate intensity. Then, R^2 value displays $0,199$. It can therefore be concluded that the percentage increase of average inventory level may explain the variability of the percentage decrease of the bullwhip effect amplification to a height of $19,9\%$. In addition, the overall explanatory power of the model isn't very important since the $R^2_{adjusted}$ displays a value of $0,154$. The authors concluded that the linear model is statistically significant $(F = 4.465; ddl = 19; Sig. < 0.05)$ but doesn't fit very well the simulated data. Despite the linear regression isn't well adjusted to the simulated data, both the constant and the explanatory variable are significant at the 5% risk threshold when looking at Table 7. Thus, the authors suggested to perform some non-linear models to check if another model will be more suitable for the simulation results. As shown in Table 8, the authors checked the performance of 9 models and they selected the better one in terms of R^2.

Table 8. Models of the relationship linking the percentage decrease of the bullwhip effect amplification and the percentage increase of average inventory level

Model		R-squared
Exponential		19,23%
Linear		19,90%
Logarithmic		22,14%
Power		22,07%
Polynomial	2nd degree	19,59%
	3rd degree	27,75%
	4th degree	31,73%
	5th degree	38,28%
	6th degree	38,65%

Table 8 shows that the 6th degree polynomial model outperforms the rest of the tested models. Since the value of R^2 increases to reach 38,65%, this model explains the highest variability of the dependent variable Y (the percentage decrease of the bullwhip effect amplification). Figure 4 shows the illustration of this model, fitting much better the scatter graph.

Figure 4. Illustration of the 6th degree polynomial model

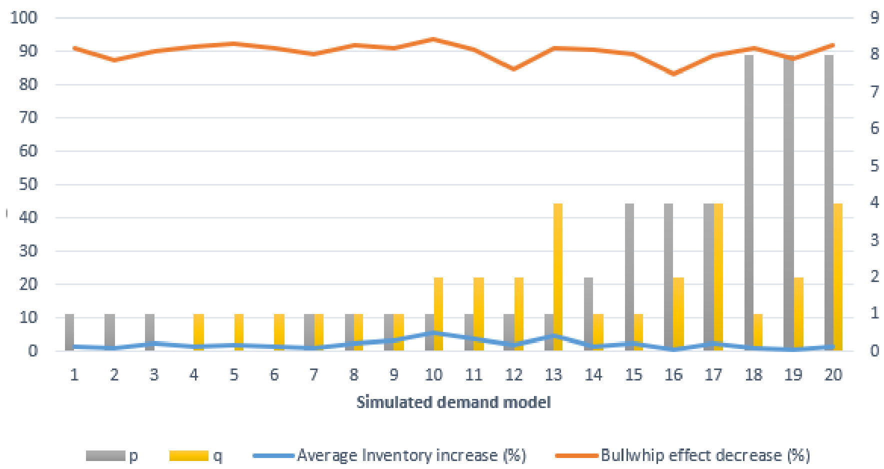


The 6th degree polynomial model is expressed by equation (5) as follows:

$$\hat{Y} = -0,0543X^6 + 1,1863X^5 - 10,222X^4 + 44,149X^3$$
$$-99,831X^2 + 111,11X + 42,777 \quad (5)$$

The 6th degree polynomial model is the most adjusted among the tested models. This model captures in a polynomial form, about 38,65% of the complex behavior linking the bullwhip effect amplification to the upstream average inventory level. The authors assume that increasing the number of demand models simulated can improve the explanatory power of the model. However, as shown in Figure 5, there is no apparent relation between ARMA's autoregressive and moving average parameters p and q on one hand, and the variation of the performance indicators on the other hand. It means that the demand's time-series structure, in this context, doesn't affect the behavior of the supply chain performance, as it was reported in the works of Ali et al. (2017) and Tliche et al. (2020).

Figure 5. Supply chain performance variation according to the demand's time-series structure



5.4 Approach's Resilience to Supply Chain Parameters

In this subsection, the authors discuss the effect of varying lead-times, shortage and holding costs on supply chain performance. These parameters are generally considered as performance indicators in supply chains (Pochampally et al. 2009). Let:

$$D_t = 10 + 0,200\,D_{t-1} - 0,150\,D_{t-2} + 0,120\,D_{t-3} - 0,100\,D_{t-4} + 0,080\,D_{t-5} + 0,070\,D_{t-6}$$
$$+0,060\,D_{t-7} - 0,051\,D_{t-8} + \xi_t + 0,100\,\xi_{t-1} + 0,060\,\xi_{t-2} + 0,040\,\xi_{t-3} + 0,010\,\xi_{t-4}$$

be the demand of a final customer arriving at the downstream actor.

Figure 6. Supply chain performance according to different lead-times

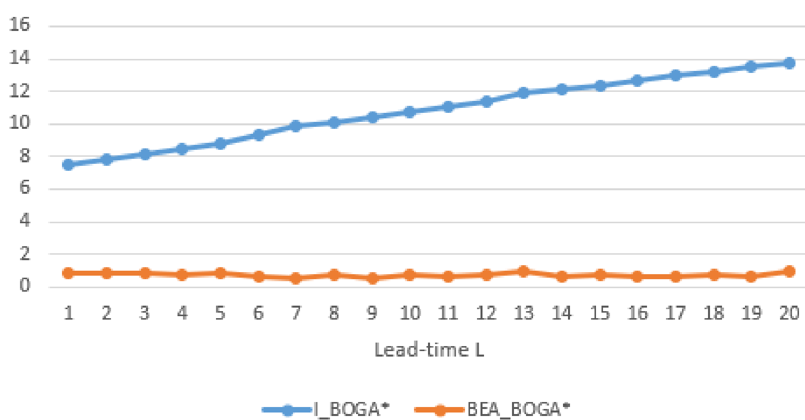


Figure 6 shows the results of varying lead-time L in a range of [1; 20] when $N = 12$, $h = 1$ and $s = 2$, on the two performance indicators. As expected, the average inventory level increases when the lead-time L increases. However, the bullwhip effect isn't affected by the increase of the lead-time since the indictor is showing the performance of the star-solution in each instance. This finding implies a strong conclusion as it outperforms most of the results reported in the literature. Even in times of transport or logistics crisis, the performance in terms of bullwhip effect of the whole supply chain can be maintained at a certain level.

Figure 7. Supply chain performance according to different holding costs

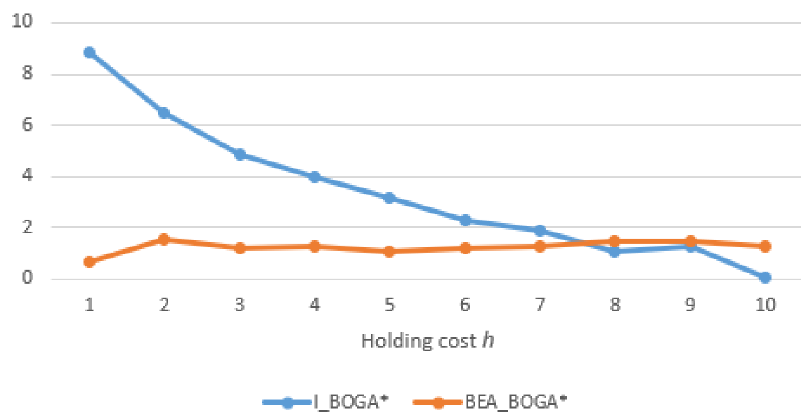
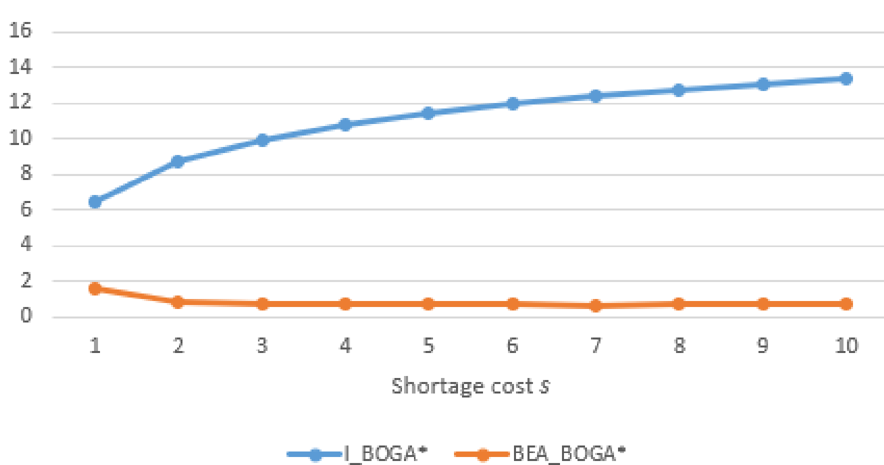


Figure 7 shows the results of varying the unitary holding cost h in a range of [1; 10] when $L = 5$, $N = 12$ and $s = 2$. Once again as expected, the figure shows that average inventory level decreases when unitary holding cost increases. However, in terms of bullwhip effect, the performance of the supply chain appears to be insensitive to variations of unitary holding costs.

Figure 8. Supply chain performance according to different shorting costs



Finally, Figure 8 shows the results of varying the shortage cost s in a range of [1; 10] when $L = 5$, $N = 12$ and $h = 1$. While, Figure 8 shows the positive correlation linking the average inventory level to unitary shortage cost, the bullwhip effect appears to be unaffected by the different shortage costs.

In conclusion, in the case of a DDI strategy where the WMA/BOGA* is implemented at the downstream actor's forecasts, the bullwhip effect occurring at the whole supply chain is unaffected by some well-known sources of risk such as increased holding costs, increased shortage costs or increased delivery times, while the upstream average inventory level seems dependant of such variations.

5.5 Algorithm's Robustness to Initialization

In this sub-section, the authors discuss the robustness of the BOGA to varied initializations. Indeed, the authors check the effect of varying initial population (affecting the number of generations), on the average distance of the Pareto solutions and the spread of the Pareto front (Deb, 2011). First, the number of generations indicates the elapsed time. As this indicator increases, the elapsed time is more important. Second, the spread measure indicates the change/movement in two fronts. As the spread indicator increases, the pareto front changes significantly from one generation to the next. Third, the average distance indicates the distribution' nature of the Pareto-solutions. As the average distance measure increases, the solutions on the Pareto front are unevenly distributed.

The authors keep the same numerical example of demand shown in previous sub-section 5.4 and investigate the mentioned indicators for 47 simulations. The initial population is performed using a uniform random number generator in the range of [0;1]. The values of the population size and the range of the initial population are used to create the initial population. The population size is equal to 15 × number of variables (in this case $15 \times 12 = 180$). The results of these simulations are reported in Figure 9.

Figure 9. Algorithm's robustness faced to variable initial solution

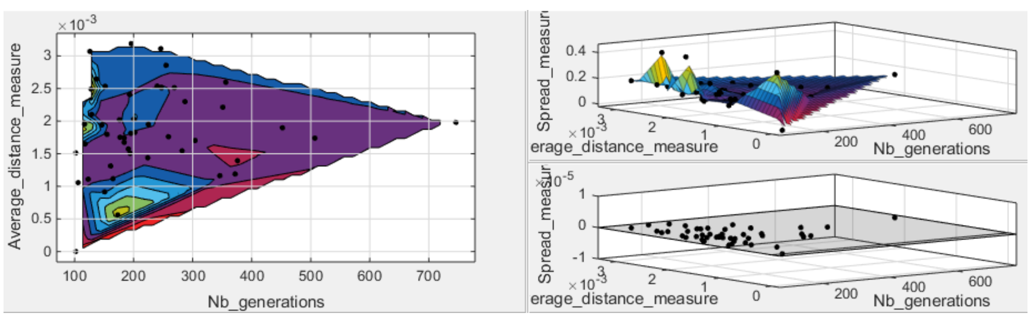
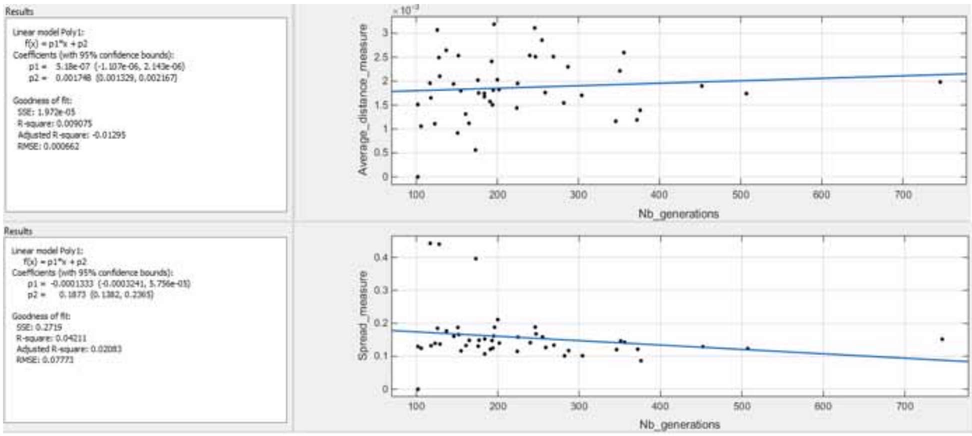


Figure 9 shows the contour, the main and the residual scatter plots of the interpolant linear surface fitting, respectively, where each point in the graphs corresponds to a different initial solution represented by a 3D-vector of the resulting number of generations, the average distance and the spread indicator after the run of the algorithm. While as expected, the number of generations highly depends on the initial solution (in the range of [100; 800]), the results show the insignificant variability in terms of both average distance of the Pareto solutions (in the range of [0; 0,0035]) and spread (in the range of [0; 0,45]). These results are further confirmed by Figure 10, where the linear regressions of the two performance indicators on the number of generations are insignificant in terms of R^2 and $R^2_{adjusted}$.

Figure 10. Results of linear regression of the number of generations on the average distance and spread measures



In conclusion, the BOGA doesn't present any particular dependence on initialization when it comes to spread indicator or average distance measure. The only indicator that changes depending on the initial population is the number of iterations or the elapsed time.

5.6 Managerial Implications for Multi-Level Supply Chains

In terms of managerial implications, all actors of a decentralized multi-level supply chain, i.e., operations managers at any supply level, can coordinate their forecasting operations with other levels in order to achieve a better overall performance. During the forecasting processes, the n-1 actors (see Figure 2) can convince actor 1 to adopt a forecasting method that allows the demand process to be inferred. Similar in principle to the SMA method, the WMA method allows such inference. Moreover, if all actors can introduce WMA for their forecasts, any upstream actor will be able to infer the demand at any downstream level. The essence of this paper is first the parameterization of the weighting vector in the WMA method in a manner to achieve the common goal of reducing the bullwhip effect. The BOGA makes it possible to obtain a set of undominated solutions according to the two discussed objectives. Besides, the DDI approach where WMA/BOGA* is adopted, appears to be robust in terms of bullwhip effect, with regard to possible variations in supply and delivery conditions. The practical part of drawing the Pareto front and selecting the star-solution will theoretically be up to the actor 2 if his average inventory function presents a confidential information. This is usually the case when actor 1 isn't in favor of sharing the customer's demand information.

An engineering or operations manager can benefit from the findings of this study by coordinating the forecasting method with his formal upstream actor, his formal downstream actor, or both of them. The authors thus distinguish three cases of figure:

- If an operations manager coordinates his forecasting approach with his formal downstream actor, he will automatically benefit from the improvements of both average inventory level and bullwhip effect, which results in forecasting accuracy and economic savings.
- If an operations manager coordinates his forecasting approach with his formal upstream actor, a contract including the savings' sharing induced by the adoption of the DDI approach must be established between the two partners.
- If an operations manager coordinates his forecasting approach with both downstream and upstream actors, he will be able to benefit doubly from this coordination by cumulating the advantages of the first two cases.

In addition to the possibility of a local collaboration between two actors of a supply chain, a second collaboration approach from a global supply chain view-point can be considered. The specific action plans based on the research findings can be highlighted by the development of a savings-sharing contract between all supply chain partners at once, which can follow the proposals below:

1. Supply chain actors (actor 2 to actor n in Figure 2) are invited to negotiate and convince actor 1 to implement WMA method for his demand forecasting. This firstly requires the estimation of savings' allocation for each partner.
2. The actor 1 accepts to adopt the WMA forecasting method. The actor 2 applies the BOGA for his BOFP resolution, generates the Pareto border, and selects the weighting solution that minimizes the amplification of the bullwhip effect, among non-dominated solutions.
3. The actor 2 transmits the star-solution that will be implemented in the actor 1's forecasting.
4. The actor 1 adopts the WMA method in his forecasts. He implements the star-solution weights in the WMA method configuration. This is potentially a generator of costs and implementation time if ever another method was adopted.
5. The actor 2 is able to infer the demand arriving at the downstream level only through orders history. If all actors adopt the WMA forecasting method, all the supply chain links are able to infer the demand process at any downstream level.
6. The generated savings, taking into account the benefits of the entire supply chain, i.e., from actor 2 to actor n, and taking into account all the costs of adopting such a collaboration strategy such as the method implementation's costs at actor 1, have to be shared equally between all the supply chain links, unless there is leader-follower links where benefit allocations can be offered unevenly.

In Figure 11, the authors present an overview of the schematical process of the collaborative WMA/BOGA* in a context of a DDI strategy.

Figure 11. Process of WMA/BOGA* action plan in a DDI strategy

In the next section, the authors present the conclusion of the paper, highlighting the main objective, features and merits, theoretical and practical implications, as well as the limitations and the natural guidelines for future research.

6. CONCLUSION

Supply chain management is a research field that integrate more and more sophistical approaches and methods, with the objective of improving global supply chain performance. This work is developed in the light of a recent strategy called "DDI", in order to tackle a well-known issue that persists in the supply chain field.

In a multi-level decentralized supply chain, a major data communication problem may be present or arise between two actors, resulting from lack of trust, confidentiality policies, or even competition. In a context where customer's demand is confidential to the retailer, the latter may not be able or simply don't want to disclose his demand information. The DDI forecasting strategy allows an upstream actor to infer the demand met by the downstream actor, without need of information sharing.

The literature showed that this strategy is able to enhance some key performance indicators such as MSE, inventory levels or bullwhip effect. Among other things, for inference to be feasible and accurate, this strategy is conditioned by the choice of the forecasting method at the downstream level. The SMA and WMA methods allow unique demand propagation all along the supply chain. While the SMA method allows the reduction of the upstream average inventory level and the bullwhip effect, the WMA method further reduces the average inventory level when the weighting vector is a configuration/solution to the upstream inventory-oriented Newton's mono-optimization. Since this vector doesn't consider equal weights of demand's historical observations, the bullwhip effect is negatively affected and the whole supply chain is hit by its amplification (Tliche et al., 2020).

Following this research course, this research paper attempts to broaden the potential of the DDI strategy, by tackling the issue of increasing bullwhip effect when WMA forecasting method is adopted, through the integration of a bi-objective optimization into the forecasting process. Instead of adopting the inventory-oriented mono-objective Newton's method, the introduction of the BOGA allows the optimization according to both upstream average inventory level and bullwhip effect amplification.

Based on simulated demand models that follow causal invertible $ARMA\left(p,q\right)$ time-series processes, the solutions derived by the BOGA allow drawing the Pareto borders, which technically provide flexibility margins for the supply chain decision-makers. In this work, the authors opted to select solutions that minimize as much as possible the bullwhip effect among these Pareto-solutions, denoted by "star-solutions". The motivation is justified by the global nature of the bullwhip effect which affects the sustainability of the supply chain links, while keeping upstream average inventory level relatively low.

To do so, the authors computed the percentages gaps separating the WMA/Newton results to the WMA/BOGA* results, in terms of average inventory and bullwhip effect. First, the authors found that a negligeable increase in the upstream average inventory level (2,16% on average) corresponds to a considerable decrease in the bullwhip effect amplification (89,92% on average). It has been noted that the average decrease of bullwhip effect amplification is nearly 44 times the increase of the upstream average inventory level. A 6^{th} degree polynomial model captured the complex relationship linking the two performance indicators and would allow supply chain decision-makers to estimate their co-variations and savings. It has also been argued that the identified polynomial model fitted the simulated data but explanation power may be subject of enhancement if more simulations are carried.

The approach adopted in this research paper has several features and merits. First, this approach is conditioned by the use of the WMA forecasting method at the downstream level, in order to ensure unique demand propagation along the supply chain. Second, the approach has made it possible to broaden the knowledge of the DDI strategy by showing that causal invertible ARMA demands' inference can be done at any downstream level of the supply chain, in a context of no explicit demand information sharing, if all actors use WMA forecasting method. Third, the approach tackles a persistent harmful effect which persists in the supply chain field. Indeed, it allowed considerable improvement in terms of bullwhip effect while ensuring low upstream inventory levels, under some specific forecasting configurations, denoted in this paper by star-solutions. Fourth, the authors verified the resilience of the approach with respect to some key supply chain parameters and algorithm's robustness. The simulations' results showed that in stressful situations of lead time, holding or shortage variations, the performance of the bullwhip effect isn't affected. However, the upstream average inventory level is dependant of these parameters. The authors also checked the robustness of the algorithm when faced to different initializations. The results showed the unsensitivity of both average distance of Pareto solutions and spread measure to different initial populations, unlike the elapsed time which significantly depends on initialization. Finally, a general managerial scheme for multi-level supply chains was proposed in order to adopt the WMA/BOGA* approach while distinguishing some cases of figure.

In terms of theoretical implications, the developed approach allows to improve the supply sustainability as the bullwhip effect affects the entire chain from the retailer to the supplier, through the various levels of manufacturers and transporters. Such approach can also improve trust and emphasize future collaboration between business partners. It also improves the resilience of forecasting processes, as the inventory level's optimization implies the forecasting MSE's optimization, and the proposed algorithm is unsensitive to initialization. This allows for example, the possible implementation of a method that randomly provides initializations, which will reduce the labour costs related to computer programming.

In terms of practical implications, the proposed approach provides two collaboration perspectives. First, from a local supply chain performance view-point, an operations manager has three options to collaborate with his business partners. As discussed in previous section, collaboration with formal downstream actor would allow benefits from the improvements of both average inventory level and bullwhip effect, while collaboration with formal upstream actor needs to be formalised through a sharing of achievable savings. The operation manager can combine the two advantages if collaboration is done with both upstream and downstream actors. Second, from a global supply chain performance view-point, if the first downstream actor who faces the end customer's demand accepts to use the WMA forecasting method, all upstream levels will automatically benefit from the reduction of the bullwhip effect. The provided polynomial model would help supply chain actors to estimate the variations of bullwhip effect with regard to the upstream inventory level.

The authors conclude the paper with limitations and natural guidelines for future research. First, the DDI strategy can still be evaluated with other forecasting methods. To date, only SMA and WMA insure unique time-series demand propagation all along the supply chain. Second, a real-case study with WMA forecasts in a DDI strategy must take place in the future for industrial validation. Third, genetic algorithms present some known limitations such as the computation time as they require many iterations as well as excessive use of the evaluation function and the allocation memory. It is also known that genetic algorithms approach the optimal Pareto-front, without having the certainty of having reached it. Other metaheuristics may be more interesting. Finally, as performance metrics in this study are limited to the manipulation of averages and standard deviations, the generalization of such a collaborative strategy in the context of seasonal autoregressive integrated moving average (SARIMA) models isn't possible. More sophisticated and theoretical performance metrics should be developed to include the latter models in the DDI strategy.

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REFERENCES

Ali, M. M., Babai, M. Z., Boylan, J. E., & Syntetos, A. A. (2017). Supply chain forecasting when information is not shared. *European Journal of Operational Research*, *260*(3), 984–994. doi:10.1016/j.ejor.2016.11.046

Ali, M. M., & Boylan, J. E. (2011). Feasibility principles for downstream demand inference in supply chains. *The Journal of the Operational Research Society*, *62*(3), 474–482. doi:10.1057/jors.2010.82

Ali, M. M., & Boylan, J. E. (2012). On the effect of non-optimal forecasting methods on supply chain downstream demand. *IMA Journal of Management Mathematics*, *23*(1), 81–98. doi:10.1093/imaman/dpr005

Arık, O. A., & Toksarı, M. D. (2021). A Genetic Algorithm Approach to Parallel Machine Scheduling Problems Under Effects of Position-Dependent Learning and Linear Deterioration: Genetic Algorithm to Parallel Machine Scheduling Problems. *International Journal of Applied Metaheuristic Computing*, *12*(3), 195–211. doi:10.4018/IJAMC.2021070109

Bayraktar, E., Sari, K., Tatoglu, E., Zaim, S., & Delen, D. (2020). Assessing the supply chain performance: A causal analysis. *Annals of Operations Research*, *287*(1), 37–60. doi:10.1007/s10479-019-03457-y

Bhattacharya, R., & Bandyopadhyay, S. (2011). A review of the causes of bullwhip effect in a supply chain. *International Journal of Advanced Manufacturing Technology*, *54*(9), 1245–1261. doi:10.1007/s00170-010-2987-6

Cai, S., Jun, M., & Yang, Z. (2010). Implementing supply chain information integration in China: The role of institutional forces and trust. *Journal of Operations Management*, *28*(3), 257–268. doi:10.1016/j.jom.2009.11.005

Caldentey, R., Giloni, A., & Hurvich, C. (2022). Performance bound for myopic order-up-to inventory policies under stationary demand processes. *Operations Research Letters*, *50*(5), 588–595. doi:10.1016/j.orl.2022.08.005

Cetindamar, D., Çatay, B., & Basmaci, O. S. (2005). Competition through collaboration: Insights from an initiative in the Turkish textile supply chain. *Supply Chain Management*, *10*(4), 238–240. doi:10.1108/13598540510612686

Chang, H., Chen, J., Hsu, S. W., & Mashruwala, R. (2018). The impact of the bullwhip effect on sales and earnings prediction using order backlog. *Contemporary Accounting Research*, *35*(2), 1140–1165. doi:10.1111/1911-3846.12401

Coppini, M., Rossignoli, C., Rossi, T., & Strozzi, F. (2010). Bullwhip effect and inventory oscillations analysis using the beer game model. *International Journal of Production Research*, *48*(13), 3943–3956. doi:10.1080/00207540902896204

de Almeida, M. M. K., Marins, F. A. S., Salgado, A. M. P., Santos, F. C. A., & da Silva, S. L. (2015). Mitigation of the bullwhip effect considering trust and collaboration in supply chain management: A literature review. *International Journal of Advanced Manufacturing Technology*, *77*(1), 495–513. doi:10.1007/s00170-014-6444-9

Deb, K. (2011). Multi-objective optimisation using evolutionary algorithms: an introduction. In *Multi-objective evolutionary optimisation for product design and manufacturing* (pp. 3–34). Springer. doi:10.1007/978-0-85729-652-8_1

Diabat, A., & Deskoores, R. (2016). A hybrid genetic algorithm based heuristic for an integrated supply chain problem. *Journal of Manufacturing Systems*, *38*, 172–180. doi:10.1016/j.jmsy.2015.04.011

Eksoz, C., Mansouri, S. A., & Bourlakis, M. (2014). Collaborative forecasting in the food supply chain: A conceptual framework. *International Journal of Production Economics*, *158*, 120–135. doi:10.1016/j.ijpe.2014.07.031

Ellram, L. M. (2010). Introduction to the forum on the bullwhip effect in the current economic climate. *The Journal of Supply Chain Management*, *46*(1), 3–4. doi:10.1111/j.1745-493X.2009.03178.x

Gilbert, K. (2005). An ARIMA supply chain model. *Management Science*, *51*(2), 305–310. doi:10.1287/mnsc.1040.0308

Hiassat, A., Diabat, A., & Rahwan, I. (2017). A genetic algorithm approach for location-inventory-routing problem with perishable products. *Journal of Manufacturing Systems*, *42*, 93–103. doi:10.1016/j.jmsy.2016.10.004

Hosoda, T., & Disney, S. M. (2006). On variance amplification in a three-echelon supply chain with minimum mean square error forecasting. *Omega*, *34*(4), 344–358. doi:10.1016/j.omega.2004.11.005

Hosoda, T., Naim, M. M., Disney, S. M., & Potter, A. (2008). Is there a benefit to sharing market sales information? Linking theory and practice. *Computers & Industrial Engineering*, *54*(2), 315–326. doi:10.1016/j.cie.2007.07.014

Jafarian, A., Rabiee, M., & Tavana, M. (2020). A novel multi-objective co-evolutionary approach for supply chain gap analysis with consideration of uncertainties. *International Journal of Production Economics*, *228*, 107852. doi:10.1016/j.ijpe.2020.107852

Jiang, D., Li, H., Yang, T., & Li, D. (2016). Genetic algorithm for inventory positioning problem with general acyclic supply chain networks. *European Journal of Industrial Engineering*, *10*(3), 367–384. doi:10.1504/EJIE.2016.076385

Kadziński, M., Tervonen, T., Tomczyk, M. K., & Dekker, R. (2017). Evaluation of multi-objective optimization approaches for solving green supply chain design problems. *Omega*, *68*, 168–184. doi:10.1016/j.omega.2016.07.003

Keshari, A., Mishra, N., Shukla, N., McGuire, S., & Khorana, S. (2018). Multiple order-up-to policy for mitigating bullwhip effect in supply chain network. *Annals of Operations Research*, *269*(1), 361–386. doi:10.1007/s10479-017-2527-y

Khan, S. A. R., Mathew, M., Dominic, P. D. D., & Umar, M. (2022a). Evaluation and selection strategy for green supply chain using interval-valued q-rung orthopair fuzzy combinative distance-based assessment. *Environment, Development and Sustainability*, *24*(9), 10633–10665. doi:10.1007/s10668-021-01876-1

Khan, S. A. R., & Ponce, P. (2021). Investigating the effects of the outbreak of COVID-19 on perishable food supply chains: An empirical study using PLS-SEM. *International Journal of Logistics Management*.

Khan, S. A. R., Razzaq, A., Yu, Z., Shah, A., Sharif, A., & Janjua, L. (2022b). Disruption in food supply chain and undernourishment challenges: An empirical study in the context of Asian countries. *Socio-Economic Planning Sciences*, *82*, 101033. doi:10.1016/j.seps.2021.101033

Kim, S., Jang, D., Jun, S., & Park, S. (2015). A novel forecasting methodology for sustainable management of defense technology. *Sustainability*, *7*(12), 16720–16736. doi:10.3390/su71215844

Kumar, A., Mukherjee, K., & Kumar, N. (2013). A decision support system for control mechanism of inventory in a dynamic supply chain system considering supply-price trade-off using control theory. *International Journal of Business Performance and Supply Chain Modelling*, *5*(3), 308–324. doi:10.1504/IJBPSCM.2013.055741

Kumar, R., Ganapathy, L., Gokhale, R., & Tiwari, M. K. (2020). Quantitative approaches for the integration of production and distribution planning in the supply chain: A systematic literature review. *International Journal of Production Research*, *58*(11), 3527–3553. doi:10.1080/00207543.2020.1762019

Lee, H. L., Padmanabhan, V., & Whang, S. (1997). Information distortion in a supply chain: The bullwhip effect. *Management Science*, *43*(4), 546–558. doi:10.1287/mnsc.43.4.546

Michna, Z., Disney, S. M., & Nielsen, P. (2020). The impact of stochastic lead times on the bullwhip effect under correlated demand and moving average forecasts. *Omega*, *93*, 102033. doi:10.1016/j.omega.2019.02.002

Min, S., Zacharia, Z. G., & Smith, C. D. (2019). Defining supply chain management: In the past, present, and future. *Journal of Business Logistics*, *40*(1), 44–55. doi:10.1111/jbl.12201

Nakhjirkan, S., Rafiei, F. M., & Kashan, A. H. (2019). Developing an integrated decision making model in supply chain under demand uncertainty using genetic algorithm and network data envelopment analysis. *International Journal of Mathematics in Operational Research*, *14*(1), 53–81. doi:10.1504/IJMOR.2019.096979

Nam, K., Hwangbo, S., & Yoo, C. (2020). A deep learning-based forecasting model for renewable energy scenarios to guide sustainable energy policy: A case study of Korea. *Renewable & Sustainable Energy Reviews*, *122*, 109725. doi:10.1016/j.rser.2020.109725

Nguyen, D. T., Adulyasak, Y., & Landry, S. (2021). Research manuscript: The Bullwhip Effect in rule-based supply chain planning systems–A case-based simulation at a hard goods retailer. *Omega*, *98*, 102121. doi:10.1016/j.omega.2019.102121

Pochampally, K. K., Gupta, S. M., & Govindan, K. (2009). Metrics for performance measurement of a reverse/closed-loop supply chain. *International Journal of Business Performance and Supply Chain Modelling*, *1*(1), 8–32. doi:10.1504/IJBPSCM.2009.026263

Shoukohyar, S., & Seddigh, M. R. (2020). Uncovering the dark and bright sides of implementing collaborative forecasting throughout sustainable supply chains: An exploratory approach. *Technological Forecasting and Social Change*, *158*, 120059. doi:10.1016/j.techfore.2020.120059

Shumway, R. H., & Stoffer, D. S. (2017). ARIMA models. In *Time series analysis and its applications* (pp. 75–163). Springer. doi:10.1007/978-3-319-52452-8_3

Tai, P. D., Duc, T. T. H., & Buddhakulsomsiri, J. (2019). Measure of bullwhip effect in supply chain with price-sensitive and correlated demand. *Computers & Industrial Engineering*, *127*, 408–419. doi:10.1016/j.cie.2018.10.027

Tliche, Y., Taghipour, A., & Canel-Depitre, B. (2019). Downstream Demand Inference in decentralized supply chains. *European Journal of Operational Research*, *274*(1), 65–77. doi:10.1016/j.ejor.2018.09.034

Tliche, Y., Taghipour, A., & Canel-Depitre, B. (2020). An improved forecasting approach to reduce inventory levels in decentralized supply chains. *European Journal of Operational Research*, *287*(2), 511–527. doi:10.1016/j.ejor.2020.04.044

Trisna, T., Marimin, M., Arkeman, Y., & Sunarti, T. (2016). Multi-objective optimization for supply chain management problem: A literature review. *Decision Science Letters*, *5*(2), 283–316. doi:10.5267/j.dsl.2015.10.003

Verma, M., Jain, R., & Jaggi, C. K. (2022). Impact of Price-Sensitive Demand and Premium Payment Scheme on Bullwhip Effect. *International Journal of Information Systems and Supply Chain Management*, *15*(1), 1–24. doi:10.4018/IJISSCM.289225

Wang, F., Lai, X., & Shi, N. (2011). A multi-objective optimization for green supply chain network design. *Decision Support Systems*, *51*(2), 262–269. doi:10.1016/j.dss.2010.11.020

Wesonga, R., Nabugoomu, F., & Masimbi, B. (2014). Airline delay time series differentials: Autoregressive integrated moving average model. *International Journal of Aviation Systems, Operations and Training*, *1*(2), 64–76. doi:10.4018/IJASOT.2014070105

Wu, D., Teng, J., Ivanov, S., & Anyu, J. (2021). Empirical assessment of bullwhip effect in supply networks. *International Journal of Information Systems and Supply Chain Management*, *14*(2), 69–87. doi:10.4018/IJISSCM.2021040104

Yang, P. (2022). Information Management in the Logistics and Distribution Sector Using Metaheuristic Techniques. *International Journal of Information Systems and Supply Chain Management*, *15*(4), 1–21. doi:10.4018/IJISSCM.305850

Yang, Y., Lin, J., Liu, G., & Zhou, L. (2021). The behavioural causes of bullwhip effect in supply chains: A systematic literature review. *International Journal of Production Economics*, *236*, 108120. doi:10.1016/j.ijpe.2021.108120

Yeh, W. C., & Chuang, M. C. (2011). Using multi-objective genetic algorithm for partner selection in green supply chain problems. *Expert Systems with Applications*, *38*(4), 4244–4253. doi:10.1016/j.eswa.2010.09.091

Zhang, X. (2004). Evolution of ARMA demand in supply chains. *Manufacturing & Service Operations Management*, *6*(2), 195–198. doi:10.1287/msom.1040.0042

APPENDIX: PARETO-OPTIMAL SOLUTIONS OF SIMULATED PROBLEMS

Figure 12. Pareto-optimal solutions of BOFPs 1 and 2

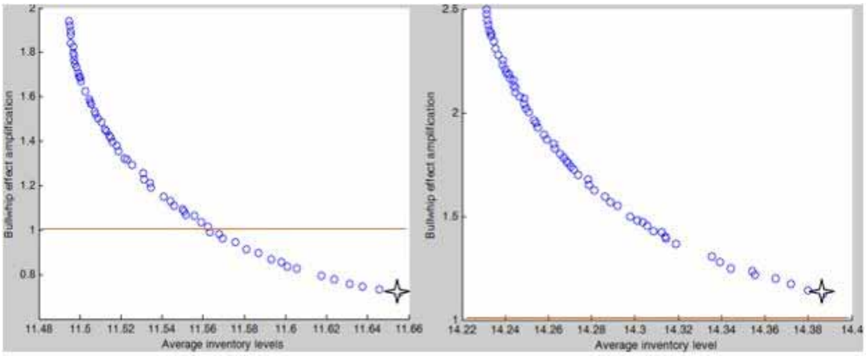


Figure 13. Pareto-optimal solutions of BOFPs 3 and 4

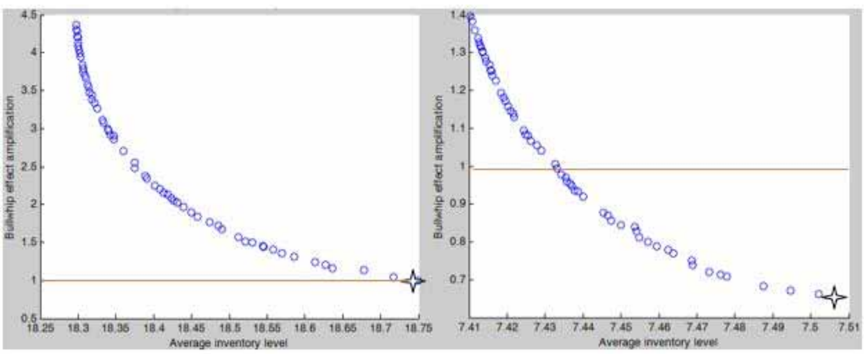


Figure 14. Pareto-optimal solutions of BOFPs 5 and 6

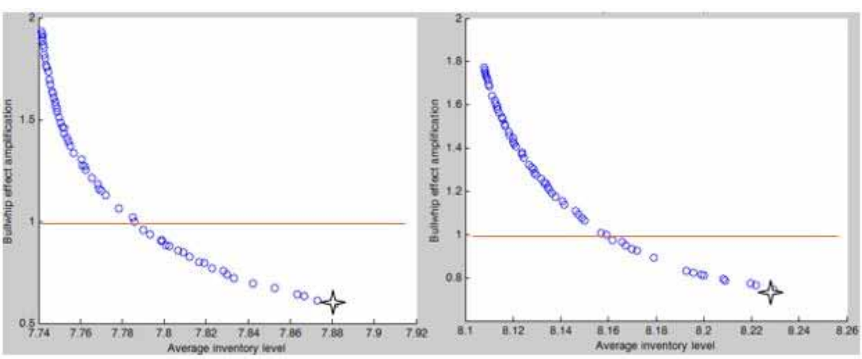


Figure 15. Pareto-optimal solutions of BOFPs 7 and 8

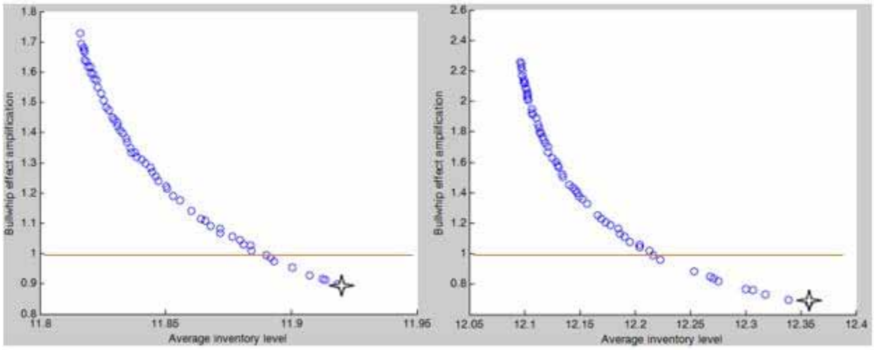


Figure 16. Pareto-optimal solutions of BOFPs 9 and 10

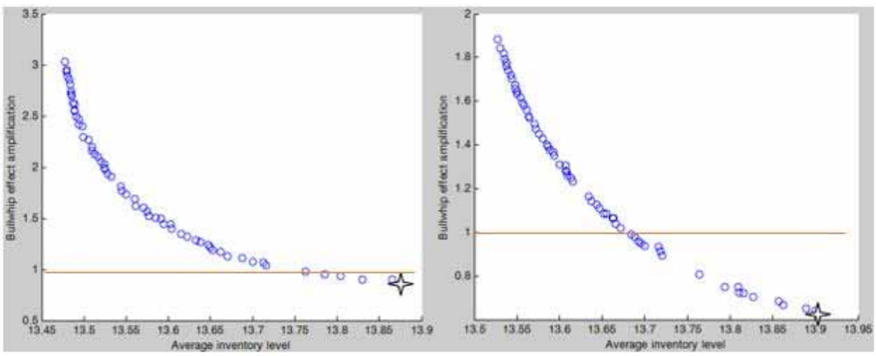


Figure 17. Pareto-optimal solutions of BOFPs 11 and 12

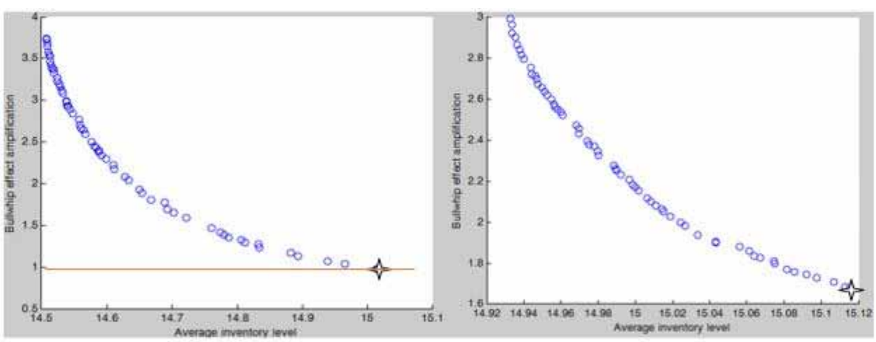


Figure 18. Pareto-optimal solutions of BOFPs 13 and 14

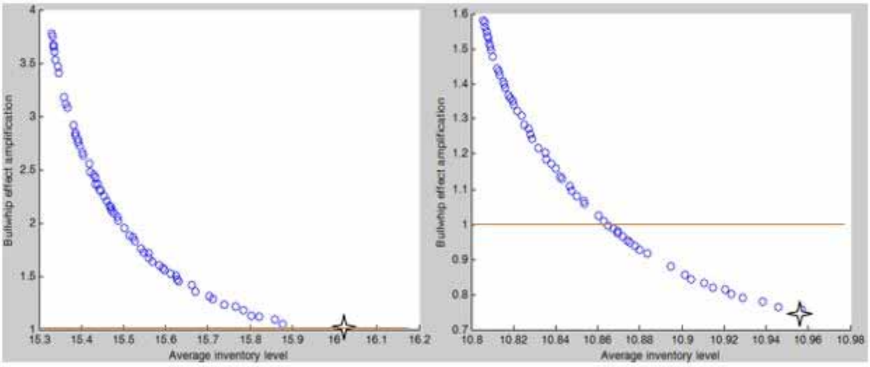


Figure 19. Pareto-optimal solutions of BOFPs 15 and 16

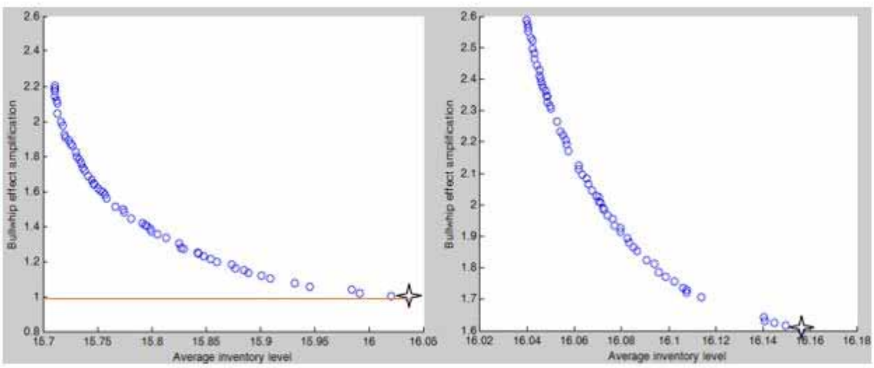


Figure 20. Pareto-optimal solutions of BOFPs 17 and 18

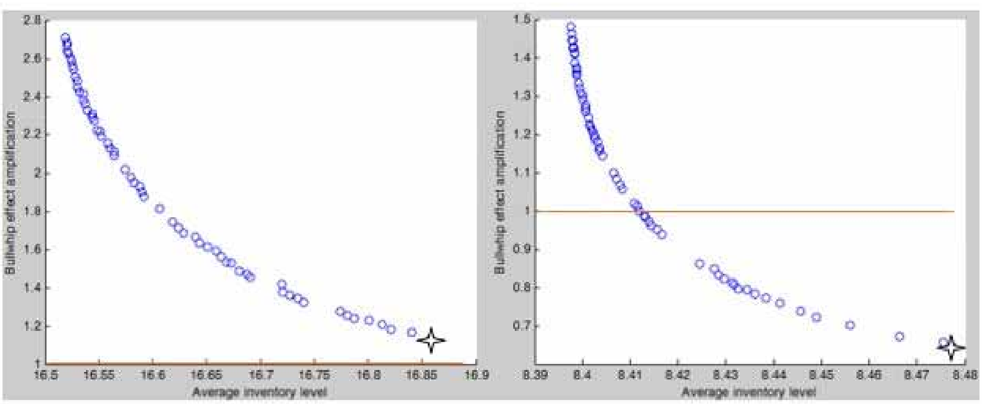
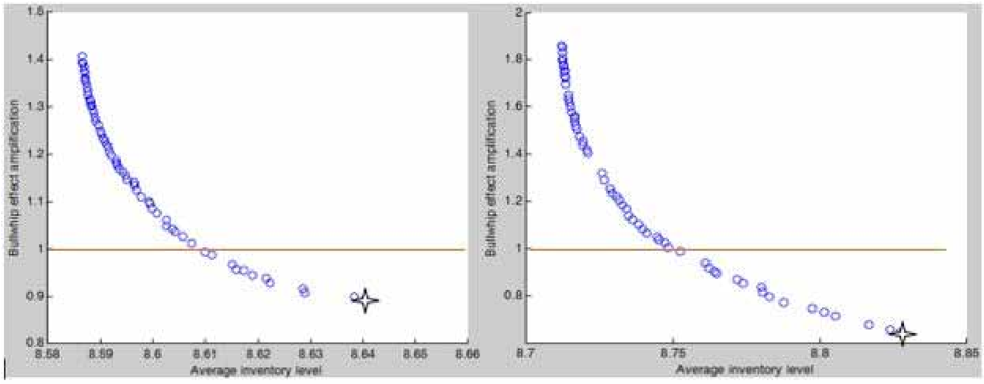


Figure 21. Pareto-optimal solutions of BOFPs 19 and 20



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