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A new data-driven framework to select the optimal replenishment strategy in complex supply chains

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Abstract: Motivated by the high variability of markets occurred in the last years, which in turns determined significant uncertainty in lead times and supply chain dynamics, this paper introduces a data-driven framework based on machine learning and metaheuristic optimization to dynamically select the most suitable replenishment strategy for a complex two-echelon (supplier-inventory-factory) supply chain (SC) problem with perishable product and stochastic lead times. Since the supplier dispatches the product (*i.e.*, the raw material) with a fixed expiration date, the product shelf-life strictly depends on the related delivery lead time, which is subject to uncertainty. In addition, a minimum order quantity has to be fulfilled and the time between two consecutive orders cannot be less than one month. The aim of the work is to select the most suitable replenishment strategy able to minimize the average stock level, which is a surrogate cost metric, while respecting a target fill rate. Considering a smoothing order-up-to policy, the data-driven prediction-optimization framework makes use of Artificial Neural Network (ANN) and Particle Swarm Optimization (PSO) to select the best replenishment parameters (*i.e.*, forecasting factor, proportional controller and safety stock factor) able to dynamically enhance the SC economic performance under the fill rate constraint. The ability of the framework under the predictive and the optimization perspective is assessed and a sensitivity analysis on the influence of replenishment parameters is presented as well.

Keywords: Supply chain dynamics; perishable product; disruption; machine learning; metaheuristic algorithm; cyber-physical system; simulation; optimization.

1. INTRODUCTION

Supply chains are large and complex systems that have been gathering a great attention from both academics and industrial practitioners during the last years. Their complexity is due to multiple sources of uncertainty and non-linear effects, which may involve unpredictable disruptions that in turns may drastically affect the performance of the whole system. Uncertainty in SC environments has been recently amplified by the COVID-19 pandemic, which caused high variability on manufacturing capability as well as on the delivery lead-times. In some contexts (such as semiconductor, food or pharmaceutical), product perishability may represent an additional source of complexity as the units of product cannot be stored infinitely without deterioration and, at the end of the related shelf life, they have to be wasted (Billaut, 2011; Acevedo-Ojeda et al., 2020). In order to face the risk of disruptions, the main objective of SC managers is to build resilient supply chains capable of reacting to the different sources of uncertainty (Razavian et al., 2021). In general, a way to achieve resilience in SC consists in selecting an optimal replenishment strategy to react to the continuous changes in market demands or delivery lead times caused by disruptive events. The aim of this paper is to introduce a data-driven framework, which exploits a prediction-optimization approach based on artificial intelligence to identify the most suitable replenishment strategy for a one-product two-echelon SC characterized by stochastic lead times and a perishable product.

1.1 Literature background

In the SC management field, the supply chain dynamics is a literature stream focused on studying counter-intuitive behavior of the SC network and effectively managing the operations of each node, such as the production and distribution operations (Framinan, 2021). The main decision problem in supply chain dynamics consists of establishing the replenishment order strategy to be adopted by the nodes of the SC. Several different replenishment strategies exist in literature; however, the Order-Up-To (OUT) policy is widely adopted in literature and in real-life supply chains. It consists of ordering a quantity of product to the downstream node so as to achieve a target inventory level and delivery work-in progress (Disney and Lambrecht, 2008). This policy allows increasing the operational performance while limiting the stock level, but the reduction of the bullwhip effect in terms of order variance is limited (Gaalman, 2006). As a consequence,

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a Smoothing OUT (S-OUT) policy is preferable in which a proportional controller parameter is used to properly adjust the order quantity (*e.g.*, Framinan, 2021; Corsini et al., 2022a, b).

The replenishment strategies and their implications on the supply chain dynamics have been mainly studied through the control theory (Lin et al., 2018) or by means of simulation techniques (Costa et al., 2020). Interestingly, Priore et al. (2019) used a machine learning algorithm (specifically an inductive learning algorithm) to dynamically select the best replenishment policies in a single-product supply chain dynamics problem with deterministic delivery lead times. Precisely, they used such algorithm to select the most suitable proportional controller to reduce the bullwhip effect. The other parameters involved in the S-OUT replenishment rule, *i.e.*, safety stock factor and forecasting factor, were fixed and not considered in the resolution problem. As a major finding, they demonstrated that this dynamics approach overperform the static alternatives.

1.2 Research contribution

Inspired by a real-life issue in the semiconductor context, the present paper deals with a two-echelon SC dynamics problem, wherein the first echelon covers the material/information flow between the supplier and the firm's inventory and the second echelon pertains the relationship between the firm's inventory and the manufacturing plant. The leading features of the problem at hand are in the following:

- The units of product are subject to perishability;
- The supplier dispatches the product units with a fixed expiration date;
- The delivery lead time from the supplier to the firm is subject to uncertainty (stochastic lead time); as a result, the shelf-life of the product units is variable as it depends on the delivery lead time;
- The orders have to be issued monthly at least, while the demand coming from the manufacturing plant should be daily fulfilled;

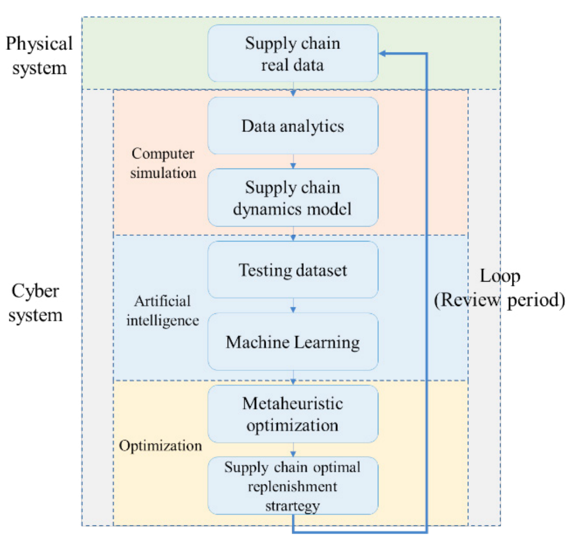

Figure 1. Diagram flow of the optimization approach for the data-driven supply chain

- Any order has to respect a minimum order quantity (*MOQ*) according to the trade agreement between the firm and the supplier.

The present paper would represent a seminal research based on some leading I4.0 paradigms, such as cyber-physical system (CPS) and data-driven optimization (DDO), with the aim of building a dynamic replenishment framework to strengthen the performance of complex supply chains. In CPSs, simulation, networking, and physical processes are simultaneously connected with each other. In brief, CPS make full use of different cyber computational systems to control a physical environment and, through a feedback control, adapt itself to new conditions, in real time (Babiceanu and Seker, 2016). On the other hand, a data-driven approach consists of making strategic decisions based on the analysis of the real-data arising from the physical environment. Consequently, DDO uses the analysis of these data to optimize the performance of the system. Metzker et al. (2021) outlined the steps of DDO, which mainly include the data analytics to process the available data and define the parameters distribution for representing the uncertainties of the problem and the mathematical formalization and modelling of the system within the perspective of a chosen optimization method.

Based on the aforementioned paradigms, the scope of the research is to introduce a data-driven framework that uses the real-life data arising from the physical supply chain system as inputs of the cyber system wherein stochastic simulation, machine learning and optimization techniques support SC managers and decision-makers in the selection of the most suitable replenishment strategy, thus favoring the resilience of the entire SC. Figure 1 depicts how the physical and cyber systems have to be interconnected and shows the steps of the DDO approach used for the supply chain dynamics problem at hand. In brief, each day a vast amount of real-life supply chain data (*e.g.*, product demand, stock level, deliveries, etc.) is collected. After a review period, the data are analyzed to update the related statistical distributions, thus capturing new changes in terms of magnitude and variability. Then, a SC dynamics simulation model is used to replicate the behavior of the system at varying replenishment strategy and used to generate the training data for the Machine Learning (ML) tool, which in turns allows building a prediction model to be embedded within a metaheuristic algorithm. This latter makes use of the ML prediction model to select the optimal parameters to be adopted for the smoothing replenishment strategy. In fact, differently from the simulation model, the regression model allows the metaheuristic to efficiently evaluate the performance of each candidate solution in a reasonable computational time. Precisely, the optimization approach will return the most suitable values of three SC control parameters which characterize the S-OUT replenishment policy, *i.e*, the forecasting factor, the proportional controller and the safety stock factor. The main contribution of the paper consists in introducing a cyber system framework that integrates simulation modelling, machine learning (specifically artificial neural networks) and metaheuristic algorithms (specifically particle swarm optimization). However, product perishability and stochastic lead times further feed the novelty of the contribution. The

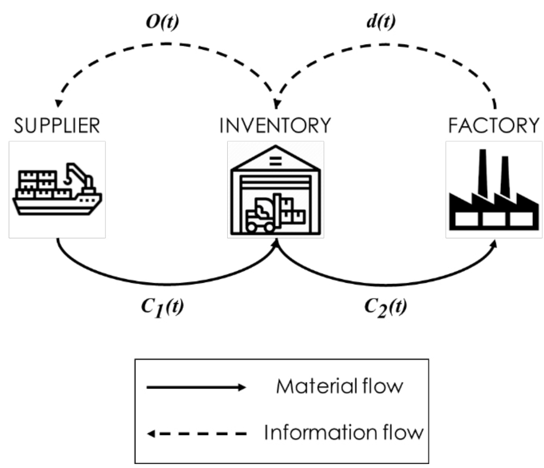

Figure 2. Supply chain model

structure of the paper is as follows. Section 2 describes the problem statement. Section 3 introduces the optimization approach combining Artificial Neural Networks (ANNs) and the Particle Swarm Optimization (PSO). Section 4 analyzes the results of the optimization approach and presents a sensitivity analysis involving a series of influencing factors. Finally, Section 5 includes the conclusions of the paper and the future research directions.

2. PROBLEM STATEMENT

The problem at hand consists of a one-product two-echelon supply chain model, as described in the previous section (see Figure 2). The first echelon stands for the supplier (i=1) and the second for the firm's inventory (i=2). Product perishability and lead time variability in the first echelon increase the complexity of the SC at hand. Since the product is released by the supplier with a fixed expiration date, the shelf-life at the inventory stage strictly depends on the delivery time, which is notably uncertain. At the second echelon, the inventory has to satisfy the demand of product arising from the manufacturing plant. As for the inventory stage, orders to the supplier are placed by adopting the S-OUT policy and the time-interval between two consecutive orders cannot be smaller than 30 days (*i.e.*, 1 month). In addition, a minimum order quantity (*MOQ*) has to be fulfilled. The supplier has infinite capacity, so no restriction affects the order coming from the firm's inventory. The units of material are delivered to the inventory with stochastic delivery lead times, which can vary in the interval $[LT_{MIN}, LT_{MAX}]$ (Gutierrez-Alcoba et al, 2017). Conversely, the delivery lead times from the inventory to the factory is negligible.

The mathematical formalization of the problem and the simulation model are based on discrete-time difference equations, which are typically adopted in the supply chain dynamics literature (Costa et al., 2020; Corsini et al, 2021, 2022a). In our model, a time unit (t) stands for one day, while the index m represents one month. For the sake of brevity, the dynamics equations are not reported in this work as most of them can be easily retrieved in the SC dynamics literature (see *e.g.* Disney and Lambrecht, 2008). However, in this section we focus only on two new equations, the former being related to the inventory level (which has to include the quantity of expired product), the latter regarding the order to supplier (that must be subject to the provided *MOQ*). The inventory level $I_2(t)$ at time t is formalized by Eq. 1, where $I_2(t-1)$ is the previous inventory level at time $t-1$, $C_1(t-LT(t))$ is the amount of product finally delivered by the supplier after the stochastic lead time $LT(t)$), $d(t)$ is the demand from the factory and $P_2(t)$ is the waste at time t (*i.e.*, the quantity of expired product).

$$I_2(t) = I_2(t-1) + C_1(t-LT(t)) - d(t) - P_2(t) \tag{1}$$

The inventory is characterized by batches of product with different shelf life, as in the paper of Polotski et al. (2021). Differently from their work, in this research the shelf life is variable and depends on the stochastic delivery lead time according to the following equation:

$$N(t)=N_{MAX} - LT(t) \tag{2}$$

where $N(t)$ is the shelf life at time t and N_{MAX} is the maximum shelf life. On the other hand, the order to the supplier at time t (i.e., $O_2(t)$), is configured as in Eq.3, where *S-OUT* means the smoothing order-up-to replenishment policy depending on the following three control parameters: forecasting factor (α), proportional controller (β), safety stock factor (ε).

$$O_2(t) = \begin{cases} S\text{-}OUT & \textbf{if } O_2(t)>MOQ \textbf{ and } \sum_{\tau=t-m-1}^{t-1} O_2(\tau)=0 \\ 0 & otherwise \end{cases} \tag{3}$$

Precisely, α is used to estimate the future demand $\hat{d}_2(t)$, as follows:

$$\hat{d}_2(t) = \alpha \cdot \sum_{\tau=t-m-1}^{t-1} d(\tau) + (1 - \alpha) \cdot \hat{d}_2(t - m) \tag{4}$$

ε is used to calculate the target inventory $TI_2(t)$:

$$TI_2(t) = \varepsilon \cdot \hat{d}_2(t) \tag{5}$$

while β is directly used in the S-OUT equation:

$$O_2(t) = max\{\hat{d}_2(t) + \beta \cdot (TI_2(t) - I_2(t) + TW_2(t) - W_2(t)\} \tag{6}$$

in which $W_2(t)$ is the delivery work in progress and $TW_2(t)$ is the target delivery work in progress. As mentioned before, $O_2(t)$ must be greater than *MOQ* and m=30 days have to elapse from the previous order, at least.

The performance metrics considered in this paper are the fill rate (*FR*) and the average inventory level ($\overline{I_2}$).

$$FR = \left(\frac{1}{T-T_{WARM}} \cdot \sum_{t=T-T_{WARM}+1}^{T} \frac{C_2(t)}{d(t)}\right)\% \tag{7}$$

$$\overline{I_2}= \frac{1}{T-T_{WARM}} \cdot \sum_{t=T-T_{WARM}+1}^{T} I_2(t) \tag{8}$$

where $C_2(t)$ is the quantity of product dispatched from the inventory to the factory to satisfy the demand $d(t)$. To avoid the randomness effect in the performance evaluation, both indicators are calculated without considering the warm-up period T_{WARM} in the simulation time horizon T. Actually, in order to select the optimal replenishment parameters, I_2 has to be minimized while keeping *FR* higher than a target fill rate denoted as FR_t. Hence, the objective function (Y) to be minimized has been configured as follows:

$$Y = |\bar{I}_2| \cdot [1 + (FR_t - min(FR_t, FR))]^q \quad (9)$$

where q is the exponent of the penalty function.

3. ARTIFICAL INTELLIGENCE BASED APPROACH

This section presents the proposed artificial intelligence-based approach, which rises from a combination between Artificial Neural Network (ANN) and Particle Swarm Optimization (PSO) algorithm.

3.1 Artificial Neural Network

In this work, to estimate how the replenishment parameters affect the performance of the SC, an ANN for regression was developed. An ANN is a machine learning algorithm inspired by the behavior of the human brain when it is stimulated by external inputs. Generally, an ANN is a network composed by an input layer, at least one hidden layer and an output layer. The input layer gathers the experimental data of the problem. In the problem at hand, the input variables are the three control parameters, *i.e.*, forecasting factor (α), proportional controller (β) and safety stock factor (ε). The first hidden layer makes use of the input data to feed another hidden layer or the final output layer. In any hidden layer, data are elaborated by several processing components, called neurons. In our AI structure, the ANN implies 2 hidden layers, each one consisting of 5 neurons. Neurons are interconnected by links and each link is characterized by a weight. Indeed, such links are used by the neurons to feed forward the processed data. The weights of the links are automatically adjusted by the ANN algorithm to enhance the behavior of the system (Lu et al., 2021). Particularly, a log-sigmoidal activation function is used to convert the weighted sum of the input signals into output signals (Nayran, 1997). In addition, the Levenberg-Marquardt Backpropagation algorithm is used for training the neural network, *i.e.*, to adjusts the weight values with the aim of minimizing the cost function of the neural network. Finally, the output layer consists of the output variable. Since two performance indicators are considered (*i.e.*, *FR* and $\bar{I}_2$), two different ANNs were developed. For both ANN models, 80%, 10% and 10% of the entire datasets were used for training, validation and testing purposes, respectively.

3.2 Particle Swarm Optimization

The PSO algorithm is a well-known metaheuristic computational method in which each particle is a candidate solution, while the swarm collects a population of particles (Kennedy and Eberhart, 1995). In this research, the population size was set to 20 particles and each particle consists of a combination of the control parameters of the supply chain (*i.e.*, α, β, ε). Each candidate solution is evaluated by means of the objective function (see Eq. 9) in which the values of fill rate (*FR*) and average inventory level ($\bar{I}_2$) are derived by the non-linear regression models generated by the related ANN meta-models. The space of solutions is explored and exploited at each iteration by varying the position and the velocity of each particle, which in turns depends on the previous position, on the best local position achieved so far (p_{best}) and on the best global position achieved by the swarm (g_{best}). Hence, in order to achieve a new local optimum, each particle moves on the basis of two distinct mechanisms: *i*) a learning mechanism according to which the particle learns by its experience, *i.e.*, by the p_{best}; *ii*) a communication mechanism according to which the particle communicates with the g_{best}. Learning and communication components are regulated by two acceleration coefficients, denoted by C1 and C2, respectively. Also, the weight assigned to the previous position is denoted as inertia coefficient w. The PSO configuration used in this paper has been set as follows. The inertia coefficient equal to 1 reduces iteration-by-iteration by 0.1% until a lower bound equal to 0.3 is achieved, while both C1 and C2 were set to 2. The exit criterion of the algorithm is based on the maximum number of iterations, which was set to 200, after a set of preliminary tests.

4. EXPERIMENTS AND RESULTS

This section presents the experimental results obtained by using the proposed AI package for the complex supply chain dynamics problem under investigation. All computational components, *i.e.*, simulation, ANN and PSO have been implemented in Matlab R2021b®. In order to generate the input data for ANN, 300 different scenarios in terms of triplets ($\alpha, \beta, \varepsilon$) values were simulated and replicated 5 times. For each scenario, the time horizon and warm-up time are equal to 3000 and 300, respectively. As for the data analytics step, the daily factory demand is derived from a normal distribution with μ_d = 100 and σ_d = 10. The delivery lead time is stochastic with LT_{MIN} = 60 and LT_{MAX} = 120 time units, while the shelf-life is equal to N_{MAX} = 180 time unit. The minimum order quantity *MOQ* is set to 7000 units of product. As for the control parameters to be optimized, α ranges in [0, 1], β varies in [0.3, 1] (as preliminary simulations revealed that frequent backlogs occur when β is lower than 0.3), while ε ranges in [2, 12]. It is worth pointing out that ε values have been normalized in the range [0, 1] before being used for ML and optimization. Figure 3 depicts the regression plots related to training (a) and testing (b) for each machine learning model. The machine learning regression models for both performance indicators (*FR* and $\bar{I}_2$) guarantee a coefficient of determination R^2 for training, testing and validation in the range [0.99, 1]. To infer about the effect of the target fill rate on the optimization of the SC replenishment parameters, four different FR_t values have been considered, namely 100%, 99%, 98% and 97%. Figure 4 shows the convergence graphs for *Y* (Figure 4a), FR (Figure 4b) and $\bar{I}_2$ (Figure 4c) as FR_t changes. Looking at the objective function *Y*, it seems that PSO assures a very fast convergence, with the exception of FR_t=100% that needs a higher number of iterations to converge. Despite of the aforementioned findings, Figures 3b and 3c show that the target fill rate and the optimal inventory level are achieved relatively later than *Y*. The optimal values of each control parameter are reported in Table 1 where it is clear that the safety stock factor is quite sensitive to the target fill rate variation. Specifically, a greater ε is needed as FR_t grows. On the other hand, the forecasting factor and the proportional controller should be set to the highest value when FR_t is lower than 100%. Instead, both of them should drastically decrease when a target FR equal to 100% has to be guaranteed.

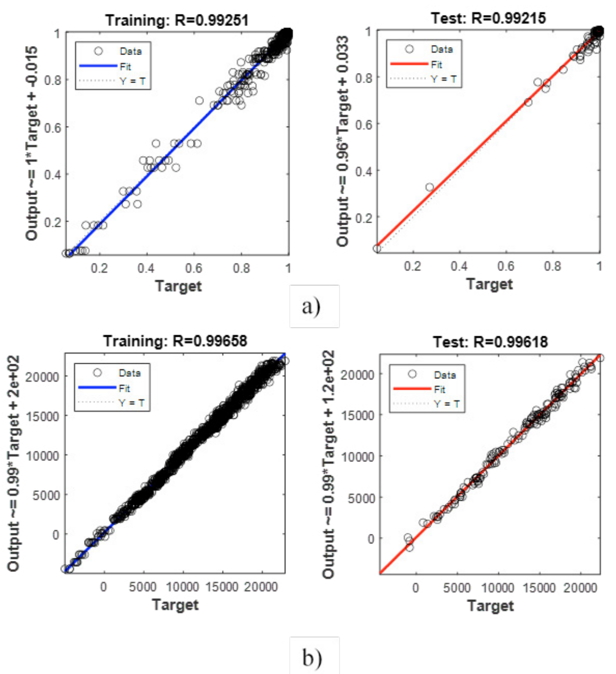

Figure 3. Regression plots of the machine learning models for (a) fill rate and (b) average inventory level

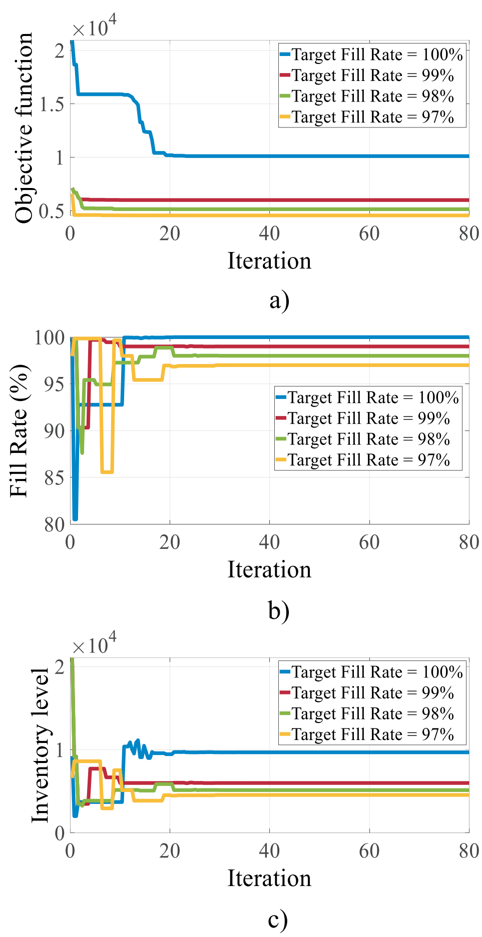

Figure 4. The convergence graphs for the cost objective function (a), the fill rate (b) and the inventory level (c)

Table 1. The best parameter values for each target fill rate

Repl. parameters/FR_t	97%	98%	99%	100%
Forecasting factor (α)	1.000	1.000	1.000	0.407
Proportional controller (β)	1.000	1.000	1.000	0.726
Normalized (actual) safety stock factor (ε)	0.023 (2.23)	0.043 (2.43)	0.074 (2.74)	0.318 (5.18)

Finally, a sensitivity analysis was accomplished to evaluate how the control parameters influence the two performance indicators (*i.e.*, *FR* and $\overline{I}_2$). A full-factorial design of experiments (DOE) was arranged in which the replenishment parameters vary by a discrete value equal to 0.1. Therefore, $11 \cdot 8 \cdot 11 = 968$ different configurations were considered. Besides, 5 replicates at varying random seeds have been executed for each configuration. The two ANN predictive models were used to evaluate the performance of each configuration in terms of *FR* and $\overline{I}_2$. Figures 5 and 6 depict the main effect plots for *FR* and $\overline{I}_2$, respectively. Both figures clearly reveal that any performance indicators are insensitive to α. On the other hand, high values of both β and ε allow to increase the fill rate and the average inventory level, as well. Interestingly, by matching Table 1 with Figures 5-6 it emerges that selecting the best replenishment parameters able to minimize $\overline{I}_2$ while keeping FR above a target value is a challenging objective, which cannot be solved by simple graphical analyses.

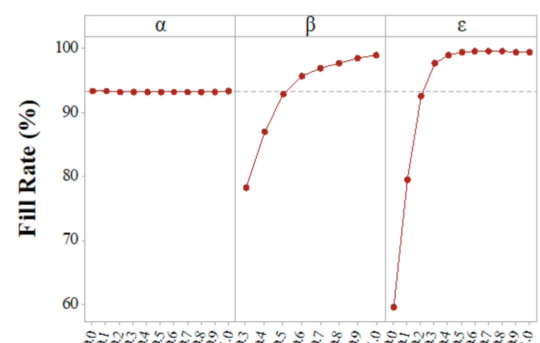

Figure 5. The main effect plot in terms of fill rate

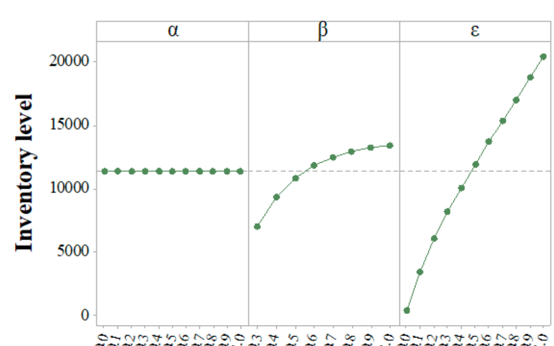

Figure 6. The main effect plot in terms of average inventory level

5. CONCLUSIONS

This work would represent a first attempt of designing a cyber-physical system in which the real-life supply chain interacts with a data-driven prediction-optimization framework to find the most suitable S-OUT replenishment parameters. Specifically, a data-driven framework which combines simulation, machine learning and metaheuristic optimization, is introduced for dynamically selecting the optimal replenishment strategy in SC problem with a perishable product and stochastic delivery lead times. Since the supplier dispatches the product with a fixed expiration date, uncertain lead times make the product shelf-life variable. Besides, any order can be placed at least one month later the previous one and a minimum order quantity has to be fulfilled. The main computational steps of the proposed data-driven framework are: *i*) a simulation model based on discrete-time difference equations to generate the input data-set for the machine learning algorithm; *ii*) ANN for regression as machine learning tool to generate the surrogate model of the supply chain dynamics problem under investigation; *iii*) metaheuristic optimization to select the best replenishment parameters of the S-OUT strategy capable of minimizing the average inventory level while assuring a target fill rate. An experimental campaign has been arranged by generating a large dataset for training the ANN models pertaining to the fill rate and the average stock level. Particularly, four different values were considered for the target fill rate, namely 100%, 99%, 98% and 97%. The experimental outcomes reveal that the forecasting factor and the proportional controller should be set to 1, when the target fill rate is lower than 100%. On the other hand, if the target fill rate must be 100%, the forecasting factor and the proportional controller should be equal to 0.41 and 0.73, respectively. Interestingly, a sensitivity analysis on the replenishment parameters shows that the forecasting factor does not significantly influence both the average inventory level and the fill rate as well. Future research will be oriented to extend the proposed framework to a dynamic and iterative configuration that allows tuning the replenishment parameters at fixed time intervals. In this context, ripple effects could be introduced thus emphasizing the adding-value of the data-driven approach over more traditional methods. Finally, applying the proposed data-driven approach to optimize the replenishment in a real-world supply chain context would be desirable as a further experimental validation.

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