MONTE CARLO SIMULATION BASED PERFORMANCE ANALYSIS OF SUPPLY CHAINS

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ABSTRACT

Since supply chain management is one of the most important management practices that impacts the financial results of services and companies, it is important to optimize and analyze the performance of supply chains. Simulation provides a way to get closer to real life complex situations and uses less simplifications and assumptions than needed with analytical solutions. This paper proposes the application of Monte Carlo simulation based optimization and sensitivity analysis of supply chains to handle modeling uncertainties and stochastic nature of the processes and to extract and visualize relationship among the decision variables and the Key Performance Indicators. In this article the authors utilize their own interactive simulator, SIMWARE, capable to simulate complex multi-echelon supply chains based on simple configurable connection of building blocks. They introduce a sensitivity analysis technique to extract and visualize the relationships among the decision variables and key performance indicators. . The proposed robust sensitivity analysis is based on an improved method used to extract gradients from Monte Carlo simulation. The extracted gradients (sensitivities) are visualized by a technique developed by the authors. The results illustrate that the sensitivity analysis tool is flexible enough to handle complex situations and straightforward and simple enough to be used for decision support.

KEYWORDS

Multi-echelon supply chain, service level, safety stock, Monte Carlo simulation, sensitivity analysis, optimization, visualization

1. INTRODUCTION

Supply chain management (SCM) is a major component of competitive strategy to improve organizational competitiveness and profitability [1]. However studies show that despite of the fact that companies consider supply chains one of their most important processes they also evaluate them as the first candidate for improvement. The literature on SCM that deals with methodologies and technologies for effectively managing a supply chain is vast. In recent years, the performance measurement, evaluation and metrics have received much attention from researchers and practitioners [2]. Effective supply chain management comprises the following main functions: setting objectives, evaluating performance, and determining future courses of actions [3]. Setting objectives and creating predictive tools to create alternative course of actions play a very important role in the success of an organization and they affect strategic, tactical and operational planning and control. These areas have not received adequate attention from researchers or practitioners. In this paper a novel framework is presented to promote a better

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understanding of how an integrated approach works and how it can improve the overall effectiveness of the supply chain and the organization as a whole.

1.1. Supply chain performance management

Our research has been motivated by the energy industry that is very heavily using effective supply chain to fulfill service level agreements providing continuous service for the customers and finish projects on time and in budget. Effectiveness of Supply chains present significant visible impact of distribution, purchasing, and supply management on company assets. Supply chain systems use, MRP (Material Requirement Planning) with ERP (enterprise resource planning) systems [4]. The concept of supply chain management (SCM) represents the current state in the evolution of logistics activities. At the operational level the main focus is on efficiency in buying, storing and distributing goods. At the strategic level, SCM brings together a lot of rapidly expanding disciplines that are transforming the way of planning and controlling logistics operations. Our intention was to create a methodology that is providing a strategic decision support tool and connecting strategic planning with operations. SCM systems use ERP software and this creates an opportunity for data mining and data driven modeling.

Since supply chain performance impacts the financial results of services and companies, it is important to analyze and optimize supply chain processes. Our premise is that firms have to take action by linking their performance measurement system to their SCM practices in order be better positioned and have more success in supply chain performance improvement and therefore to become a more profitable enterprise. Studies show that the best approach for controlling SCM systems is based on the Balanced Scorecard methodology. The intent of using the Balanced Scorecard methodology is to provide a more comprehensive monitoring system for companies by analyzing the firm's performance based on a multi dimensional landscape of Key Performance Indicators. To get a better understanding of the relationships between decision variables and Key Performance Indicators (KPI) it is necessary to perform sensitivity analysis.

Logistics systems have a certain degree of uncertainty in their behavior and therefore there is a stochastic connection between the inputs and the outputs.This stochastic behavior can be analyzed and KPIs are computed according to these results. Our intention is to provide a framework by extending BCS into a dynamic Performance Measurement system and make sure that we use the interrelationship between SCM and Balanced Scorecard methodology and show how BCS can be used to assess Supply chain performance

KPIs are not simply a list of measures, but they are connected with each-other in the following different ways:

- KPIs are organized into hierarchies based on their respective area. These measure hierarchies contain KPIs that are connected to each other and calculated from each other. There is another level of interconnectivity among KPIs.
- KPIs are associated with each other based on cause – effect relationships.
- KPIs are weighted and there is a relative importance relationship among them.
- There is a trade-off relationship among KPIs

Individual KPIs and hierarchies of individual KPIs belong to one BCS dimension. Individual KPIs serve the following purposes:

- Provide measurements for efficient control. They provide the output of system we can use to make decisions
- Provide a comprehensive reporting solution for management reporting
- Provide the measurements for the objectives of the BSC system

- Hierarchies provide strong relationship between KPIs. This relationship is based on numerical calculations. These connections are linear and deterministic.

Logistics systems are complex and they interact with other subsystems in the company. They have the following most important attributes which affect the modeling and system analysis approach:

- The processes are non-linear and stochastic
- System parameters (elements of state transformation matrix) can only be determined using system identification and data mining
- They have large number of components in a complex interaction
- Systems cannot be analyzed with analytical methods – therefore simulation models are necessary for system analysis and optimization

Based on the previous consideration simulation of supply chains is one of the key components in our approach. The simulation model can be analyzed from the following points of view:

- Estimate the outputs of the model
- Optimize the process based on this information
- Calculate the KPIs based on the estimated state variables
- Determine how KPIs interact and effected by the decision variables.

1.2. The proposed framework

This paper elaborates on the application of Monte Carlo (MC) simulation to analyze supply chains based sensitivity analysis to discover the connections between the input and output variables. The local sensitivity analysis method can only be used to determine the local sensitivity near a fixed nominal point. However, it does not account for interactions between variables and the local sensitivity coefficients. A global sensitivity analysis method can be applied to determine the effect of an input while all the inputs are varied [6-8]. These methods do not depend on the chosen nominal point [5-7]. Fig. 1 shows the simplified data flow diagram of the proposed method. The sensitivity analysis technique is based on the improved method used to extract gradients from MC simulations. It applies the linear least squares fit method to identify the gradients numerically. A hyper plane is fitted to the output values generated by MC simulation. The parameters of the hyper plane give the partial derivatives of the investigated output functions. The extracted gradients (sensitivities) are visualized by a technique developed by the authors.

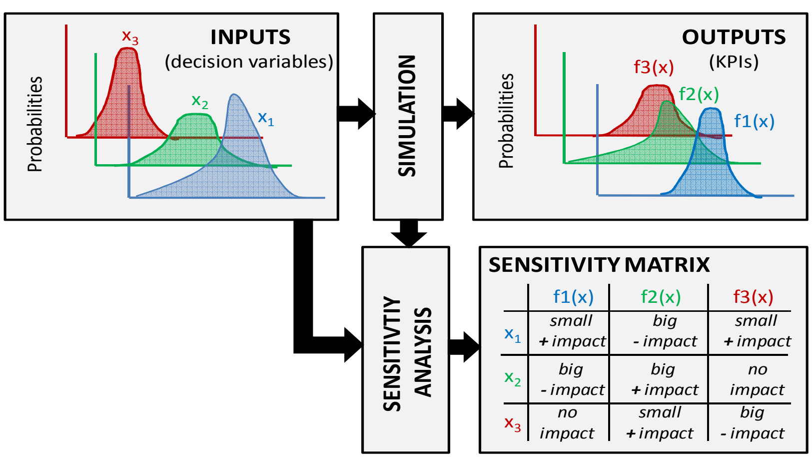

Figure 1. Simplified data flow diagram of sensitivity analysis

The paper is organized as follows. In Section 2 we revisit the problem definition of the performance improvement of multi-echelon supply chains. In this section the authors introduce an interactive simulator, SIMWARE, capable to simulate complex multi-echelon supply chains based on simple configurable connections of building blocks. In Section 3, a case study is presented. Finally, we summarize the results and the advantages of the proposed method. The results illustrate that our sensitivity analysis tool is flexible enough to handle complex situations and straightforward and simple enough to be used for decision support.

2. MONTE CARLO SIMULATION BASED SENSITIVITY ANALYSIS

Among SCM problems the modeling and simulation of inventory management systems is the most widespread in the scientific literature. Improved operation of supply chains can save billions of dollars; and effective inventory management plays an important role in this regard.

2.1. Performance improvement of multi-echelon supply chains

The idea of optimizing inventory control started with the classical economic order quantity approach. From the fifties it is a seriously researched area, Simpson [6] was the first one who formulated the serial-line inventory problem. Graves and Willems extend Simpsons work to spanning trees in [13], while in [14] they give a comprehensive review of the previous approaches for safety stock placement, the same as they propose two general approaches and introduce the supply chain configuration problem. Good overviews exist in the literature for supply chain and inventory management, like in [22], where authors give an overview of different approaches of supply chain modeling and outlines future opportunities. In [20], Lau et.al. give an overview of various average inventory level (AIL) expressions and present two novel expressions which are simpler and more accurate than previous ones. A comprehensive overview can be found in [25], where a simulation model for a real life problem with lost sales is presented, here authors consider several types of inventory policies.

The determination of safety stock in an inventory model is one of the key actions in management, Miranda and Garrido include both cycle and safety stock in the inventory model in [26], and the resulting model in this article has a non-linear objective function. Authors in [4] give a model for positioning safety stock in a supply chain subject to non-stationary demand, and they show how to extend their former model to find the optimal placement of safety stocks under constant time service (CST) policy. Prékopa in [27] gives an improved model for the so called Hungarian inventory control model to find the minimal safety stock level that ensures the continuous production, without disruption.

The bullwhip effect is an important phenomenon in supply chains, authors in [21] show how a supply chain can be modeled and analyzed by colored Petri nets (CPN) and CPN tools and they evaluate the bullwhip effect of the surplus of inventory goods, etc. using the beer game as demonstration. More recent research can be found in [1], which shows that an order policy applied to a serial single-product supply chain with four echelons can reduce or amplify the bullwhip effect and inventory oscillation.

Miranda et. al. investigate the modeling and optimization of a two echelon supply chain system in two steps [26], a massive multi-echelon inventory model is presented by Seo [30], he introduces an order risk policy for general multi-echelon system to minimize the operation cost of the system. A really complex system is examined in [31], where it is necessary to apply some clustering for similar items, because detailed analysis - considering each item individually is impossible.

The simulation-based approach was published only in the last decade. Jung et. al. [18] make Monte Carlo based sampling from real data, and they propose optimization by the modification of safety stock under service level constraints using gradient-based search algorithm, authors in [19] discuss how to use simulation to describe a multi-level inventory system. They present genetic algorithm to optimize a five-level simulation model. Schwartz et. al. [29] demonstrate the internal model control (IMC) and model predictive control (MPC) algorithms to manage inventory in uncertain production inventory and multi-echelon supply/demand networks.

The stability of the supply chain is also a recently seriously researched area, [25] shows that a linear supply chain can be stabilized by the anticipation of the future inventory and by taking the inventories of other suppliers into account, Vaughan in [32] presents a linear order point/lot size model that with its robustness can contribute to business process modeling.

A complex instance of inventory model can be found in [16], where various orders following different distribution patterns for the lead time. Sakaguchi in [28] investigates the dynamic inventory model with discrete demands varying period by period. The author gives an algorithm to solve several examples.

2.2. The Stochastic Warehouse Model

In this section, we give an overview of the warehouse model and inventory policy we have investigated Fig. 2 shows the classical inventory control model.

Replenishment Lead time (L) is the time between the *Purchase order* and the goods receipt, where $\bar{d}_L$ denotes the average demand during L. This average demand can be computed as $\bar{d}_L = \bar{d} \cdot L$, where $\bar{d}$ is the daily average demand. Using the same logic d_L is Total Demand over Lead time, when service level is 100% d_L equals to consumption. We will use d_L to denote the consumption.

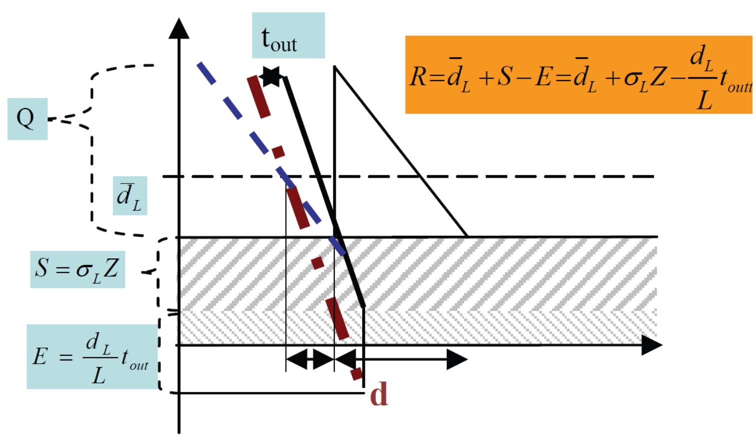

Figure 2. The classic model of inventory control

The *Cycle time* (T) is the time between two purchase orders. Q is the *Order Quantity* where $Q = d \cdot T$, i.e. it is the ordered quantity in a purchase order. We denote the *Safety Stock* by S which is needed if the demand is higher than expected (line d in Fig.1). In our special case, S is to cover the stochastic demand changes, and for a given *Service Level* this is the maximum demand can be satisfied over *L*. We also have *Maximum Stock Level* which is the stock level necessary to cover the *Expected Demand* (dashed line) in period *T*.

The *Reorder Point* (*R*) is the stock level where the next purchase order has to be issued. It is used for materials where the inventory control is based on actual stock levels. In an ideal case *R* equals to total of safety stock and average demand over lead time: ($R = \bar{d}_L + S$).

Average Stock (*K*), assuming constant demand pattern over the cycle time, can be calculated as follows:

$$K = \frac{Q}{2} + S \tag{1}$$

It is calculated as a weighted average of stock levels over the cycle time.

Service Level (*SL*) is the ratio of the satisfied and the total demand (in general it is the mean a probability distribution), or in other words it is the difference between the 100% and the ration of unsatisfied demand:

$$SL = 100 - 100\frac{(d_L - R)}{Q} \tag{2}$$

We assume that all demand is satisfied from stock while available stock exists. When we reach stock level R the demand over the lead time (d_L) will be satisfied up to *R*. Consequently, if $d_L > R$, we are getting out of stock and there will be unsatisfied demand, Therefore the service level will be lower than 100%. d_L is unknown and it is a random variable. The probability of a certain demand level is $P(d_L)$. Based on this, the service level is calculated as follows:

$$SL = 100 - 100\frac{\int_{\bar{d}_L}^{d_{\max}} P(d_L)(d_L - R)d_L}{Q} \tag{3}$$

where d_L is continuous random variable, and $d_{\max}$ is the maximum demand over lead time.

Analyzing actual supply chain systems it can be discovered that the probability patterns of material flow and demand are different from the theoretical functions. Consequently we will find a difference between the theoretical (calculated) and the actual inventory movements, therefore it makes sense using an approach based on “actual” distribution function.

The applied simulator, SIMWARE uses this approach to calculate inventory movements. Modeling inventory movements using stochastic differential equations turns out to be more successful than based on the theoretical assumption that movements are following normal distribution. We propose the following model:

$$x_{L_{i31}} = x_{L_i} - W_i + u(x, R, L), \tag{4}$$

Where x_i is stock level on the i^{th} week, W_i is a stochastic process to represent consumption. This stochastic process is based on the empirical cumulative distribution function we described in the previous section. u is the quantity of material received on week i, based on purchase orders. Purchase orders quantities are calculated based on the actual inventory level (x), reorder point, and the replenishment lead-time.

Based on our experience in analyzing the studied supply chain systems we discovered that the probability functions of material flow and demand are different from the theoretical functions.

As Figure 3 shows the distribution function of an actual material consumption is significantly different from the theoretical one. Since there is a difference between the theoretical (calculated) and the actual inventory movements, it makes sense using the proposed MC simulation approach based on empirical distribution functions.

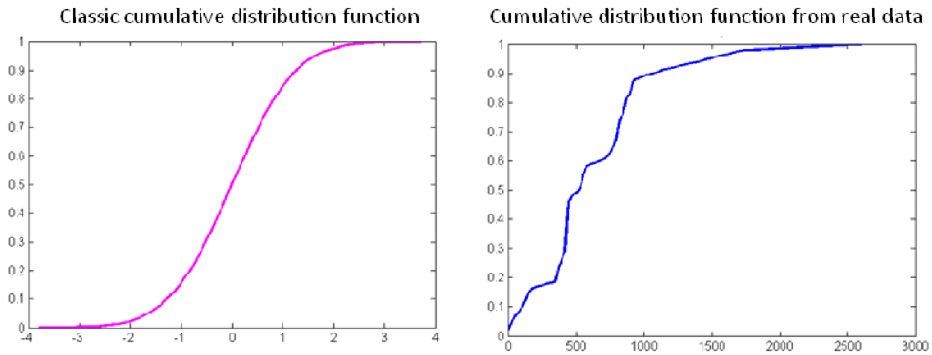

Figure 3: Theoretical and actual (right) Cumulative Distribution function for a material based on its consumption data

Our studies showed that if we want to construct a more realistic model or simulator, we need to use different distribution functions for each warehouse . These distribution functions are based on actual data extracted from the SAP Material Management (MM) module.

The SIMWARE program offers an easy-to-use interface to build even complex supply chains, and propose a novel component based structure. Using this program, users can easily optimize the supply chain, for example by the MATLAB Optimization Toolbox Sequential Quadratic Programming (SQP) functionality, but the proposed methodology gives a chance to use more effective optimization algorithms as well. Optimization process is changing the reorder point while keeping the service level at the required value. As a result we find the optimal reorder point for the given service level. This determines an optimal inventory level to minimize our current cost objective function.

2.3. Sensitivity analysis

In this subsection we introduce our method we used in our calculations related to sensitivity analysis. The expected system performance can be calculated as the average of the outputs of the simulation runs:

$$\overline{L}(v) = \frac{1}{N}\sum_{i=1}^{N} L(x,v) \tag{5}$$

where v contains the parameters of distribution functions of variables in x, L is the output function at a given input and N is the number of MC simulations. A response surface can be constructed from the realizations (or a subset) from a Monte Carlo analysis with a best fit, using standard criteria, at and near a nominal point.

The fitting of a tangent plane is a known robust procedure called linear least squares method. The n-dimensional tangent hyper plane can be defined by the following expression:

$$L_L(x) = a_0 + \sum_{i=1}^{n} a_i x_i \tag{6}$$

where a_0 and a_i are the coefficients of the fitted hyper plane, x_i is the ith input and L_L is the fitted hyper plane. The a_i coefficients are the partial derivatives of the analyzed output functions respect to x_i.

This method applies criteria to select the applicable input and output values to fit the hyper plane from a large number of MC simulations. The selection is based on the maximum likelihood of each input variable. If the all the values in an input combination are in the following region, that input is used in fitting:

$$x_{i,ml} \pm \sigma_i \tag{7}$$

where $x_{i,ml}$ is the maximum likelihood of x_i (in normal distribution it equals to the mean value), σ is the deviation of ith input.

2.3. Visualization of Sensitivities

The result of sensitivity analysis is a Jacobian matrix which contains the partial derivatives of output values (e.g. key performance indicators) based on the input variables (e.g. decision variables). If we have many variables and outputs it is hard to effectively rank the inputs because the large number of possible combinations between the inputs and outputs. In attempt to solve this issue we developed a simple visualization technique to support the ranking process.

In the first step we defined the normalized Jacobian matrix:

$$\hat{J}(i,j) = \frac{J(i,j)}{\sum\limits_{j=\{1,\ldots,n\}} \left| J(i,j) \right|} \tag{8}$$

where i and j are the row and the column numbers in the Jacobian matrix, n is the number of inputs, $\hat{J}$ is the normalized Jacobian matrix. The sum of the absolute values of a column in the new matrix is 1.

Based on the normalized Jacobian matrix color codes from blue to red is assigned to every matrix element. Blue denotes a negative connection between input and output, red shows positive cause-effect relationship.

The following is a simple example to show the proposed visualization technique using a model with three inputs and three outputs:

$$f_1(x) = 15 - 2x_1 - 5x_2 - x_1 x_2 \tag{9}$$

$$f_2(x) = 40 - (x_1 + 2)^2 - (x_2 + 3)^2 \tag{10}$$

$$f_3(x) = 1000 + 250x_1 + 100x_2 - 200x_3 + 12.5x_1 x_2 \tag{11}$$

All the input variables have normal distribution. The distribution functions parameters are summarized in Table 1.

Table 1. The parameters of distribution functions

Variable	Mean value	Deviation
x_1	10	5
x_2	20	7
x_3	50	15

The results of the analytical calculations based on the Jacobian matrix using the expected values of inputs is shown in Table 2.

Table 2. The analytical calculation results

	x_1	x_2	x_3
f1(x)	-22	-15	0
f2(x)	-24	-46	0
f3(x)	500	225	-200

The results of sensitivity analysis of simulation runs are shown in Fig.4. x1 has the biggest impact on f1(x) and it has negative effect, x2 has the second biggest impact, while x3 has no effect. This example was used to validate our methodology and show the graphical representation of the analysis.

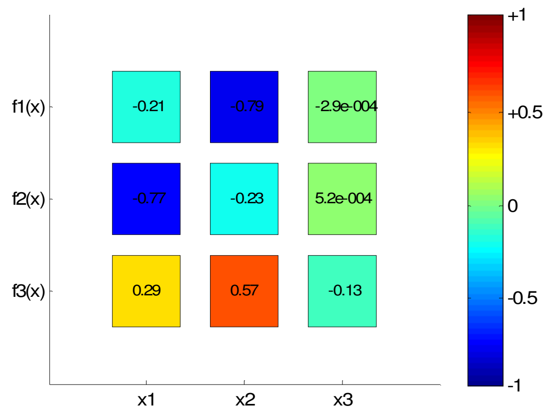

Figure 4. The visualization of sensitivity analysis

3. CASE STUDY

In this chapter we show a complete performance analysis for a 2-echelon supply chain. The parameter values of our simulation are based on data extracted from the SAP Material Management Module of E.On Business Services Ltd is used to analyze a system with two connected warehouses.

3.1. Problem Formulation

The following diagram shows the supply chain, i.e. the structure of the analyzed 2-level system. The holding cost in the second Warehouse is 30 percent higher than in the first Warehouse. Here, *x* variables are inputs (corresponds to *Q*), while *y* variables are demands. There exist 2 type of demands, one is the direct consumption by the customers (y_1, y_2) and the other is a stock transfer between warehouses (y_{12}).

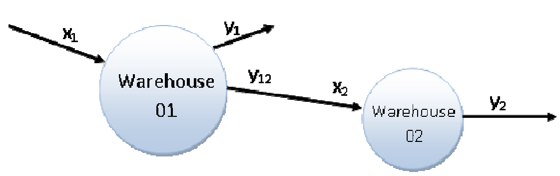

Figure 5. The analyzed 2-level system.

In Figure 6, the values of the objective function (i.e. cost) is presented as a function of the reorder point of the two Warehouses. In the optimization problem both service levels are considered as well as the constraints.

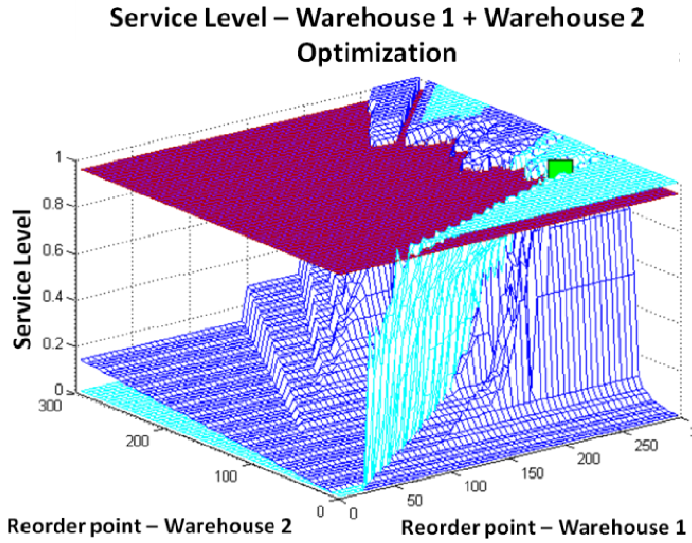

Figure 6. The result of the optimization.

Figure 6 shows the result of the optimization using the SQP method. The optimal solution is highlighted with the green square. It satisfies the 95% and 90% constraints and ensures the minimal holding cost in the warehouses. The result of the simulation runs is presented in the next figure. The fluctuations in the average inventory levels after ten MC simulations are shown, and the investigated period is 50 weeks. The service levels of both warehouses are determined, they are 0.97 and 0.89. After the optimization, the adjusted parameters makes it sure that none of the warehouses running out of stock during the investigated period.

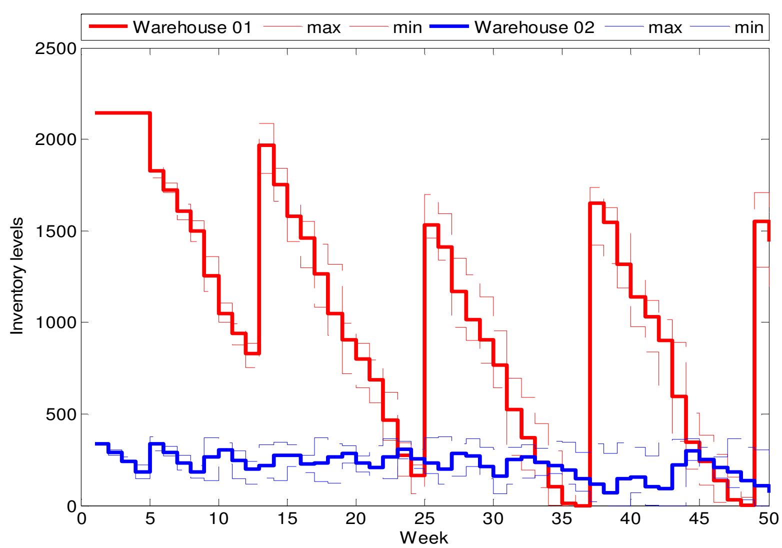

Figure 7. Inventory levels in the 2-level system.

3.2. Sensitivity Analysis

The previous subsection showed that the suggested model of the multi-echelon system can be used for optimization based on the impact analysis of changes in the stochastic input variables on the desired outputs. However, decision makers could be interested in the effects on the decision variables as well. The suggested sensitivity analysis technique could support such performance management tasks. In this paper only a demonstrative example is provided to show the applicability of the proposed technique.

The output functions in our simulation model are the following:

1. the average holding cost during the investigated period ($f_1(x)$);
2. the average inventory level in *Warehouse 01* ($f_2(x)$);
3. the average service level in *Warehouse 01* ($f_3(x)$);
4. the average inventory level in *Warehouse 01* ($f_4(x)$);
5. the average service level in *Warehouse 02* ($f_5(x)$).

We investigated the effect of the following input variables in this case study:

1. the mean value (x_1) and the deviation (x_2) in the normal distribution function of the demand in the central warehouse;
2. the mean value (x_3) and the deviation (x_4) in the normal distribution function of the demand in the local warehouse.

SIMWARE can use different input distributions, like empirical distributions shown in Figure 3. We generated the model input parameters based on normal distribution taking the effect of the uncertainty into consideration (see Table 3).

Table 3. Demand function parameters

Variable	Mean value	Deviation
x_1	60	10
x_2	15	5
x_3	50	15
x_4	10	5

MC simulations were performed to analyze the stochastic behaviour of the system. We calculated the average properties of the warehouses based on a large number of simulation runs using the following input variables:

- Length of simulation is 28 weeks
- The service levels of the warehouses are fixed, they are 97% and 89% respectively

100.000 input combinations were generated for the x [x_1 x_2 x_3 x_4] vector based on the given distribution functions and the output functions were evaluated based on these combinations. We could use only 59 input combinations for the gradient calculation, because only these combinations were in the given region.

As a result we created a Sensitivity matrix (Table 4). The results are presented as a Jacobian matrix where the connection between four input parameters and five output variables were evaluated. This matrix of the partial derivatives are accurate but not informative enough for decision makers. It is quite difficult to rank the input variables to show which one has the most impact on the output function using a matrix. In order to make the methodology more useful in decision support we developed a visualization technique to show the strengths of the connections (see Figure 8).

Table 4. Sensitivity matrix

	x_1	x_2	x_3	x_4
f1(x)	$-5.6 \cdot 10^{+3}$	$1.5 \cdot 10^{+4}$	$-1.8 \cdot 10^{+3}$	$-9.5 \cdot 10^{+3}$
f2(x)	$-8.2 \cdot 10^{0}$	$5.1 \cdot 10^{+1}$	$8.2 \cdot 10^{-2}$	$-1.1 \cdot 10^{+1}$
f3(x)	$-2.5 \cdot 10^{-2}$	$-1.7 \cdot 10^{-2}$	$-1.5 \cdot 10^{-2}$	$5.6 \cdot 10^{-2}$
f4(x)	$-6.9 \cdot 10^{0}$	$-7.3 \cdot 10^{-1}$	$-4.1 \cdot 10^{0}$	$-1.4 \cdot 10^{+1}$
f5(x)	$-8.8 \cdot 10^{-3}$	$1.3 \cdot 10^{-2}$	$-1.9 \cdot 10^{-3}$	$-2.1 \cdot 10^{-2}$

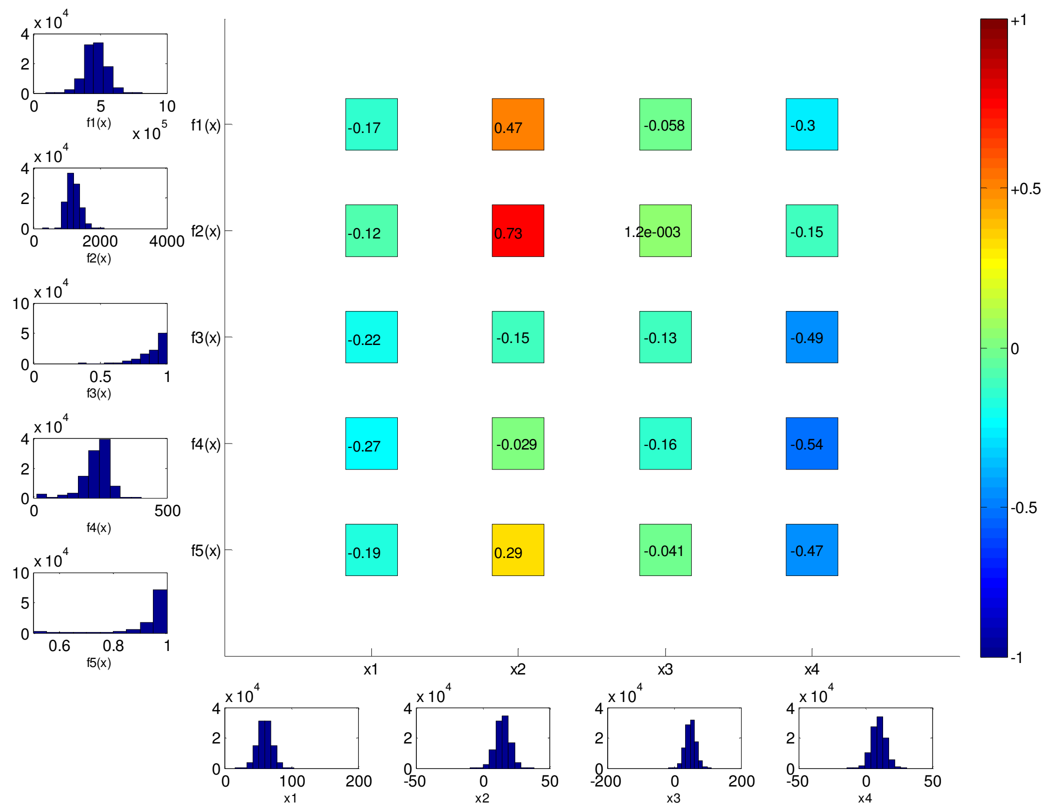

Figure 8. The result of the sensitivity analysis

As it is shown in Figure 8. the demand deviation has much bigger impact on the chosen KPIs than the mean values. Histograms next to the input variables show that the input parameter values follow normal distribution. Histograms at the output functions show the expected values and the distributions of the analyzed output functions.

This type of visualization technique can provide a very useful tool for decision makers, because they can use the results of the Key Performance Indicators based sensitivity analysis. The figure shows unambiguously which input has the utmost effect to the chosen outputs. Decision makers can choose both the input parameters and the KPIs – as outputs – and the simulation results are presented in a dashboard like format. This methodology makes the simulation a practical management tool.

4. Conclusion

Since supply chain performance impacts the financial performance of services and companies, it is important to optimize and analyze the performance of supply chains. This paper proposes the application of Monte Carlo simulation based sensitivity analysis to handle modeling uncertainties and stochastic nature of the supply chains and to extract and visualize relationship among the decision variables and the Key Performance Indicators.

In this article the authors introduce an interactive simulator, SIMWARE that is capable to simulate complex multi-echelon supply chains based on simple configurable connection of building blocks. To support the evaluation of the extracted gradients (sensitivities) a simple visualization technique is developed. The proposed method is applied in case of multi-echelon system built from two warehouses. The solution has been validated by simulating four stochastic input variables. The results illustrate that the developed sensitivity analysis tool is flexible enough to handle complex situations and straightforward and simple enough for practical decision support.

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