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Research Article

A Stochastic Decision Support System for Economic Order Quantity Problem

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Improving decisions efficiency is one of the major concerns of the decision support systems. Specially in the uncertain environment, decision support systems could be implemented efficiently to simplify decision making process. In this paper stochastic economic order quantity (EOQ) problem is investigated in which decision variables and objective function are uncertain in nature and optimum probability distribution functions of them are calculated through a geometric programming model. Obtained probability distribution functions of the decision variables and the objective function are used as optimum knowledge to design a new probabilistic rule base (PRB) as a decision support system for EOQ model. The developed PRB is a new type of the stochastic rule bases that can be used to infer optimum or near optimum values of the decision variables and the objective function of the EOQ model without solving the geometric programming problem directly. Comparison between the results of the developed PRB and the optimum solutions which is provided in the numerical example illustrates the efficiency of the developed PRB.

1. Introduction

Economic order quantity (EOQ) problem has been investigated by many researchers during the past decades. Most of the presented inventory models are developed in the deterministic environment. Pentico and Drake [1] and Khan et al. [2] reviewed deterministic economic order quantity models. But, some of the researchers considered variations in the real world situations and presented inventory models in the uncertain environments. These uncertain EOQ models can be classified into three general categories: fuzzy EOQ models, stochastic EOQ models, and hybrid EOQ models. In the fuzzy environment, Park [3] investigated the EOQ model in which the order and the inventory costs are considered as trapezoidal fuzzy numbers. The author suggested rules to transform the fuzzy cost information in precise inputs for the EOQ model. Samanta and Al-Araimi [4] developed an inventory model based on the fuzzy logic in which the periodic review model of inventory control with variable order quantity is considered. The control module combines fuzzy logic with proportional-integral-derivative (PID) control algorithm. This model simulates the decision support system to maintain the inventory of the finished product at the desired level subject to the demand variations and the uncertainties of the production system. Roy and Maiti [5] presented a fuzzy EOQ model with limited storage capacity. In the presented model fuzziness is introduced in both objective function and storage area. Authors considered demand is related to the unit price and the setup cost varies with the quantity produced/purchased. Mondal and Maiti [6] presented a soft computing approach using genetic algorithm to solve multi-item fuzzy EOQ models under fuzzy objective goal of cost minimization and imprecise constraints on the warehouse space and the number of production runs with crisp/imprecise inventory costs.

Second class of the uncertain EOQ models is stochastic economic order quantity models. In this category Friedman [7] developed classical EOQ model with finite replenishment rate under stochastic lead time assumption. Eynan and Kropp [8] presented a periodic review system under stochastic demand with variable stock out costs. Hayya et al. [9] considered demand and lead time as random variables and formulated a stochastic model to obtain optimum values of reorder point and order quantity. Hojati [10] evaluated the probabilistic-parameter EOQ model of Lowe and Schwarz [11] and the fuzzy parameter EOQ model of Vujošević et al. [12]. The author used simulation to compare the results. In the other work, a stochastic economic order quantity model over a finite time horizon is presented by Sana [13] in which the customer demand is assumed to be stochastic with predetermined probability distribution function. In this model replenishment period is considered price dependent and selling price is assumed to be a random variable that follows a probability density function. Wang [14] introduced a solution approach to obtain optimal values of the order quantity and the reorder point when the supplier capacity and the lead time demand are probabilistic. Yan and Kulkarni [15] considered a single stage production-inventory system in which production and the demand rates are stochastic with predetermined probability distribution function. De and Goswami [16] presented a probabilistic inventory model for items that deteriorate at a constant rate and the demand is a random variable. Lee and Wu [17] considered the EOQ model for inventory of item that deteriorates follows a Weibull distributed rate.

The last category of the uncertain EOQ models is which developed in the hybrid environment. Panda et al. [18] developed a multi-item economic order quantity model in which the cost parameters and the resources are estimated as fuzzy/hybrid values. They formulated this model as a geometric programming problem in which unit cost is a function of the demand rate. Wang et al. [19] proposed an economic order quantity (EOQ) problem with imperfect quality items, where the percentage of the imperfect quality items in each lot is characterized as a random fuzzy variable. They considered the setup cost per lot, the holding cost of each unit item per day, and the inspection cost of each unit item as fuzzy variables. Dutta et al. [20] proposed an inventory model in the fuzzy-stochastic environment in which demand is estimated as fuzzy random variable and order quantity must be obtained through an optimization problem as decision variable. In another research, Dutta et al. [21] presented continuous review inventory system in the mixed environment. In this study customer demand is considered as fuzzy random variable and order quantity and reorder point are considered as decision variables which should be calculated so that the total expected annual cost be minimized.

The developed models in the EOQ literature can be viewed from two distinct mathematical and managerial viewpoints. Form the mathematical viewpoint it should be emphasized that in the aforesaid uncertain economic order quantity models, parameters and coefficients of the decision variables have probability/possibility/hybrid distribution functions whereas the decision variables are considered to be crisp. This means that, in an uncertain environment, a crisp decision is made to meet some decision criteria. Therefore, obtained decisions may not support decision maker in all situations. From the managerial viewpoint, it should be said that, most of the presented EOQ models and solution approaches in the literature are focused on the mathematical programming methods. Although the optimization methods can formulate inventory problems efficiently and they give global optimum decisions, but in the some real word situations may not be applicable. It is a real fact that managers trust on the decisions which their making process be understandable. Optimization models and their solution approaches are very complex for practitioners and obtained decisions may not be acceptable for them at all time.

In this paper, an EOQ model is developed in the stochastic environment in which the holding cost, setup cost, and inventory space have probability distribution functions. Obviously, when the parameters of the EOQ model are estimated using probability distribution functions, optimum values of the order quantity, and other decision variables cannot be deterministic. In the other words, each of the uncertain parameters might be realized in the different values and optimum values of the decision variables are calculated based on these parameters. So, the decision variables of the EOQ model may have different values. Therefore, deriving a probability distribution function for each decision variable (such as order quantity) seems to be rational. For this end, we present an algorithm to obtain the optimum probability distribution functions of the decision variables and the objective function of the stochastic EOQ model. Obtained optimum probability distribution functions gathers all possible optimum values of the decision variables and the objective function regarding the future realization of the uncertain parameters. It can give a wide vision of the possible situations and solutions of the problem to the decision maker and improve his/her knowledge over the problem. Due to the complexity of the proposed probabilistic geometric programming model for the practitioners such as managers and could be a bit hard to solve for real world problems, a new probabilistic rule base (PRB) is developed as a decision support system to infer optimum or near optimum values of the decision variables without solving presented stochastic EOQ model directly. The organization of this paper is as follows. In Section 2, notations and assumptions are presented. The stochastic EOQ problem is formulated in Section 3. Section 4 consists of the developed probabilistic rule base and its designing approach. Performance of the presented PRB to obtain the optimum or near optimum solutions is illustrated via a numerical example in Section 5. Finally, in Section 6, conclusions and future researches are remarked.

2. Assumptions and Notations

Stochastic economic order quantity model is developed under following notations and assumptions.

Notations

Q: Order quantity

D: Product demand

$\tilde{c}$: Holding cost per unit per time

$\tilde{A}$: Setup cost

$\tilde{A}_0$: Setup cost per unit product

P: Unit production cost

S: The storage space for unit item

$\tilde{I}$: Available inventory space

K: Predetermined constants.

Assumptions

I: Setup cost is uncertain and its probability distribution function is predetermined.

II: Inventory holding cost is uncertain and its probability distribution function is predetermined.

III: Inventory capacity is uncertain and its probability distribution function is predetermined.

IV: Setup cost is related to the order quantity via following function:

$$\tilde{A} = \tilde{A}_0 \times Q^{\gamma}; \quad 0 < \gamma < 1. \tag{1}$$

V: Production cost has inverse relation with the demand as follows:

$$P = KD^{-\beta}; \quad \beta > 1. \tag{2}$$

Based on the above notations and assumptions, the stochastic economic order quantity model is developed in the next section.

3. Stochastic Economic Order Quantity Model

In this section economic order quantity problem under assumption explained in the previous section is developed in the stochastic environment. As mentioned before, the inventory holding cost, the setup cost, and the inventory space are stochastic in nature and estimated via proper probability distribution functions. Therefore the decision variables must be driven as uncertain decisions in the stochastic environment. In other words, we are interested in deriving the probability distributions of the objective function and the decision variables through the following model:

$$\begin{aligned} &\min \quad Z = \frac{\tilde{A}D}{Q} + PD + \frac{Q}{2}\tilde{c} \\ &\text{S.t.} \\ &\qquad SQ \le \tilde{I}, \\ &\qquad D, Q > 0, \end{aligned} \tag{3}$$

where in the objective function, the first term is the total setup cost, production cost is considered in the second term, and the third term is the total holding cost. The constraint of the model (3) represents the storage space limitation. Stochastic parameters $\tilde{A}$, $\tilde{B}$, and $\tilde{c}$ could have any type of probability distribution function subject to the problem situations.

Replacing $\tilde{A}$ and P in the model (3) by (1), and (2) respectively, yields

$$\begin{aligned} &\min \quad Z = \tilde{A} \times Q^{\gamma-1}D + KD^{1-\beta} + \frac{Q}{2}\tilde{c} \\ &\text{S.t.} \\ &\qquad SQ \le \tilde{I} \\ &\qquad D, Q > 0. \end{aligned} \tag{4}$$

Model (4) is a probabilistic geometric programming problem which can be solved using conventional stochastic programming approaches such as expected value method. These methods convert the stochastic model into a crisp equivalent and solve the crisp version instead of the original uncertain problem and present crisp values for the decision variables. As mentioned before, according to this fact, in model (4), parameters are stochastic in nature, optimum values of the decision variables must be uncertain too. So the purpose of solving model (4) with the stochastic parameters is to derive optimum probability distributions of the decision variables to minimize the objective function. Proper probability distribution functions of the decision variables and the objective function could be derived using the following algorithm.

Step 1. Randomly generate a, c and i respect to the probability distribution functions of the stochastic parameters $\tilde{A}$, $\tilde{c}$, and $\tilde{I}$ respectively and convert stochastic model (4) to the following deterministic equivalent:

$$\begin{aligned} &\min \quad Z = a \times Q^{\gamma-1}D + KD^{1-\beta} + \frac{Q}{2}c \\ &\text{S.t.} \\ &\qquad SQ \le i \\ &\qquad D, Q > 0. \end{aligned} \tag{5}$$

Step 2. Model (5) is a deterministic posynomial geometric programming problem. This model can be solved easily using standard geometric programming solution approaches. By solving model (5), optimum values of the decision variables D^* and Q^* and also the objective function Z^* will be obtained.

Step 3. Repeat steps 1 and 2 for N times where N is a sufficiently large number.

Step 4. Fit a proper probability distribution function to D^*, Q^*, and Z^* data and name them as $\overline{D}$, $\overline{Q}$, and $\overline{Z}$.

Probability distribution functions of the stochastic parameters gather all possible situations of the problem and also probability distribution functions of the decision variables provide all possible optimum solutions for the decision maker. It can give a wide vision to the decision maker over the problem and improve his/her knowledge about uncertain environment of the problem. Due to the complexity of the proposed stochastic geometric programming model for the practitioners such as managers, in the next section, a new probabilistic rule based decision support system is developed based on the obtained probability distribution functions of the decision variables. Presented DSS can help decision makers to determine optimum or near optimum value of the economic order quantity without solving geometric programming model of the EOQ problem directly.

4. Probabilistic Rule Base (PRB)

Rule bases are the powerful tools to design a decision support system to help decision makers to make a decision in different situations. The rule bases have been used in many practical studies so far. Most of these works have used stochastic rule bases as inference engine in the developed decision support system in which each crisp rule has a probability degree of the accuracy. In this paper, we develop a stochastic rule base in which the antecedents and consequents have probability distribution functions. Developed rule base is called "probabilistic rule base (PRB)." The developed PRB is used to infer the optimum or near optimum values of the variables D and Q and the objective function Z without solving the geometric programming model of EOQ problem directly. The design stages of the PRB are as follows:

(1) Determine probability distribution functions of the stochastic input parameters: In the stochastic economic order quantity problem, define the probability distribution functions of the stochastic parameters $\widetilde{A}$, $\widetilde{c}$ and $\widetilde{I}$. Stochastic parameters $\widetilde{A}$, $\widetilde{c}$ and $\widetilde{I}$ could have any type of probability distribution function subject to the problem situations. For example $\widetilde{A}$ may have an exponential probability distribution and $\widetilde{c}$ and $\widetilde{I}$ have normal probability distribution functions as shown in Figure 1.

(2) Calculate consequents: In the probabilistic rule base designed for the stochastic EOQ problem, the decision variables of model (4) are considered as consequents. Use presented algorithm in the previous section to obtain the probability distribution functions of the consequents.

(3) Rule base construction: Design three distinct probabilistic rule base (PRB) to infer the decision variables D and Q and also the objective function Z. To do this, use stochastic parameters $\widetilde{A}$, $\widetilde{c}$, and $\widetilde{I}$ as the antecedents of the each probabilistic rule base. Consider $\overline{D}$, $\overline{Q}$, and $\overline{Z}$ as the consequent of the probabilistic rule bases 1, 2, and 3 respectively.

(4) Implication method: Here, a new implication method is developed named Correlation Coefficient based Implication (CCI) method. The steps of the proposed method are as follows.

Step 1. Calculate correlation coefficient between each antecedent parameters $\widetilde{A}$, $\widetilde{c}$, and $\widetilde{I}$ and consequent. For example, in the first probabilistic rule base, calculate ρ_A^D, ρ_c^D, and ρ_I^D, respectively, as the correlation coefficients between the antecedent parameters $\widetilde{A}$, $\widetilde{c}$, and $\widetilde{I}$ and the consequent $\overline{D}$, with respect to their probability distribution functions.

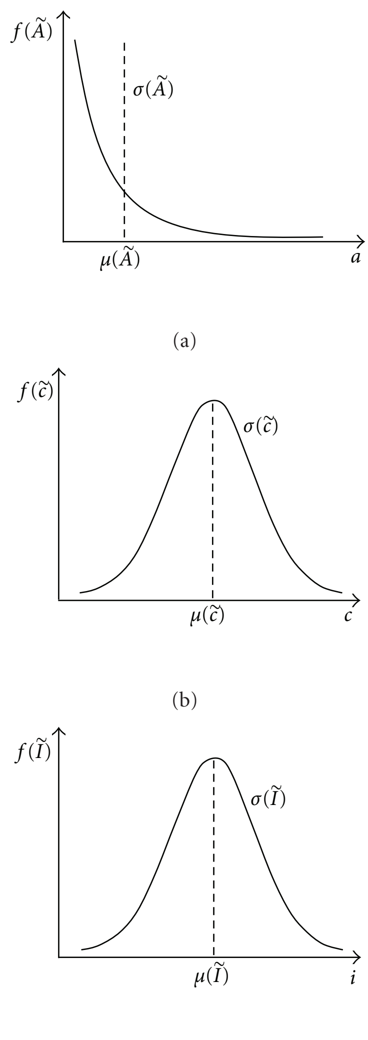

Figure 1: Probability distribution functions of one set of the stochastic input parameters $\widetilde{A}$, $\widetilde{c}$, and $\widetilde{I}$.

Step 2. Determine the most correlated parameters with the consequent. For instance, in the first probabilistic rule base put $\rho^D = \max\{|\rho_A^D|, |\rho_c^D|, |\rho_I^D|\}$ and name related parameter as φ. φ is the most correlated parameter with the consequent $\overline{D}$.

Step 3. Calculate the state probability. In the first rule base, if x_0 be the input of the candidate antecedent parameter φ, then calculate α as the state probability as follows:

$$\alpha = F_{\varphi}(x_0) = P(\varphi \leq x_0) = \int_0^{x_0} f(\varphi)\, d\varphi. \tag{6}$$

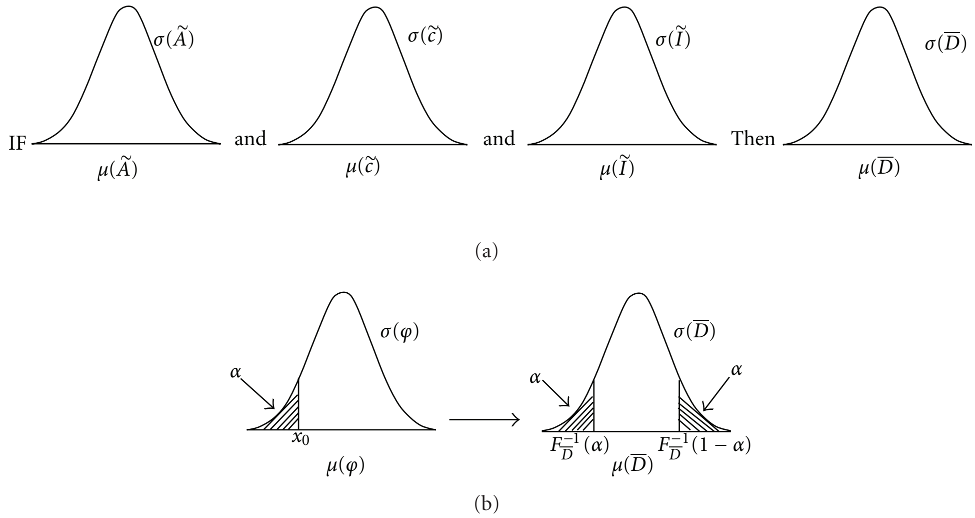

Figure 2: (a) Representation of a probabilistic rule base (PRB) to infer decision variable D; (b) the CCI method.

In the above equation, $f(\cdot)$ is the probability distribution function of the related antecedent parameter.

Step 4. Base on the correlation sign (negative or positive) between the most correlated antecedent and the consequent and the state probability value α, determine the consequent value. For example, in the first rule base, considering the correlation sign (negative or positive) between φ and consequent $\overline{D}$, one of the cases 1 or 2 will be fired to derive value of the decision variable D.

(i) *Case 1: If Correlation* $(\varphi, \overline{D}) > 0$, *then* $D = F_{\overline{D}}^{-1}(\alpha)$.

(ii) *Case 2: If Correlation* $(\varphi, \overline{D}) < 0$, *then* $D = F_{\overline{D}}^{-1}(1-\alpha)$.

For more explanations, the developed CCI algorithm is shown in Figure 2.

In the next section, we give a numerical example which shows the application of the developed PRB.

5. Numerical Example

In this section, to illustrate the efficiency of the developed probabilistic rule base a numerical example is presented and its reliability is explained subject to the obtained results. For a new product, consider several parameters as follows:

$$K = 100, \quad \gamma = 0.5, \quad \beta = 1.5, \quad S = 10,$$
$$\widetilde{A} \sim \text{Gamma}(200, 0.05),$$
$$\widetilde{c} \sim \text{Gamma}(100, 0.01), \tag{7}$$
$$\widetilde{I} \sim \text{Gamma}(3000, 0.02),$$

where Gamma(α, β) introduce gamma distribution function with parameters α and β. Gamma distribution function is a more flexible distribution so that presents a wide range of distributions. Because of this property, in this example gamma distribution function is considered for all parameters to show that the developed PRB could be implemented for any type of distribution functions.

Using above parameters, the following possibilistic GP can be formulated for this problem:

$$\begin{aligned} \min \quad & Z = \widetilde{A} Q^{-0.5} D + 100 D^{-0.5} + \frac{Q}{2}\widetilde{c} \\ \text{S.t.} \quad & \\ & 10Q \leq \widetilde{I} \\ & D, Q > 0. \end{aligned} \tag{8}$$

As mentioned before, the purpose of solving the model (8) is deriving optimum probability distribution functions of the decision variables and the objective function. Using proposed algorithm in the previous section, the proper probability distribution functions of the decision variables and the objective function can be estimated as follows:

$$\widetilde{D} \sim \text{Gamma}(418.14, 0.0128),$$
$$\widetilde{Q} \sim \text{Gamma}(2824.12, 0.002), \tag{9}$$
$$\widetilde{Z} \sim \text{Gamma}(1778.27, 0.038)$$

Based on the probabilistic parameters $\widetilde{A}$, $\widetilde{c}$, and $\widetilde{I}$ and the above decision variables and objective function, following if-then rule bases could be structured.

Table 1: Some samples solved using the developed PRBs.

E.g.	A	c	I	D^{PRB}	Q^{PRB}	Z^{PRB}	Z^*	Deviation (%)
1	11.49	0.92	59.92	4.82	5.99	71.27	70.92	0.49
2	12.12	0.95	60.09	4.63	6	72.61	72.24	0.52
3	11.13	1.01	60.44	4.94	6.04	70.48	70.42	0.10
4	9.83	0.92	60.18	5.39	6.02	67.58	67.45	0.21
5	9.56	0.80	60.49	5.49	6.05	66.97	66.45	0.79
6	10.44	0.88	59.94	5.17	5.99	68.96	68.67	0.43
7	10.67	1.17	60.46	5.09	6.04	69.47	69.96	0.69
8	10.74	1.04	58.79	5.07	5.87	69.64	69.93	0.41
9	9.61	0.89	59.27	5.47	5.92	67.08	66.99	0.13
10	9.13	0.92	59.35	5.67	5.93	65.95	65.99	0.05
11	9.99	1.05	58.54	5.33	5.85	67.96	68.42	0.67
12	9.97	1.12	61.32	5.34	6.13	67.91	68.22	0.45
13	10.77	1.03	59.00	5.06	5.9	69.71	69.94	0.32
14	11.75	1.09	59.53	4.74	5.95	71.83	72.01	0.25
15	10.70	0.95	60.26	5.081	6.03	69.56	69.39	0.25

Table 2: Results of comparison between the developed PRB outputs and the optimum solutions.

Deviation from optimum solution (%)	D	Q	Z
Minimum deviation	0.002	0	0
Maximum deviation	2.9767	0.1943	1.8618
Average deviation	0.5573	0.0414	0.4094

$$\begin{aligned}
&\text{If } \tilde{A}\sim\text{Gamma}(200,0.5) \text{ and } \tilde{c}\sim\text{Gamma}(100,0.01), \text{and } \tilde{I}\sim\text{Gamma}(3000,0.02) \text{ Then } \tilde{D}\sim\text{Gamma}(418.14,0.0128)\\
&\text{If } \tilde{A}\sim\text{Gamma}(200,0.5) \text{ and } \tilde{c}\sim\text{Gamma}(100,0.01), \text{ and } \tilde{I}\sim\text{Gamma}(3000,0.02) \text{ Then } \tilde{Q}\sim\text{Gamma}(2824.12,0.002)\\
&\text{If } \tilde{A}\sim\text{Gamma}(200,0.5) \text{ and } \tilde{c}\sim\text{Gamma}(100,0.01), \text{ and } \tilde{I}\sim\text{Gamma}(3000,0.02) \text{ Then } \tilde{Z}\sim\text{Gamma}(1778.27,0.038).
\end{aligned} \tag{10}$$

The first rule is used to infer the decision variable D and the second one is implemented for reasoning the decision variable Q. Also the objective function can be obtained using third rule.

Designed probabilistic rule bases can efficiently solve problems in the form of model (8) with deterministic parameters. 1,000 samples are generated randomly and solved by the developed PRBs and also outputs are compared with the optimum solutions. Some of these examples are presented in Table 1.

Table 2 shows results of the comparison between the decision variables and the objective function values obtained from the developed PRBs and optimum values for 1,000 randomly generated samples.

As Table 2 shows, average deviations for D, Q, and Z are 0.56%, 0.041%, and 0.41%, respectively. To demonstrate how much the value of the average deviation for 1,000 different samples is robust and also to show the pattern of the deviations dispersion, the cumulative proportion curve of the D, Q, and Z deviations are provided as Figure 3.

As it depicted in Figure 3, over than 97% of deviations between PRB outputs and optimum solutions for the decision variable D are less than 1.5% and for decision variable Q over than 96% of deviations are less than 0.1%. Also, Figure 3(c) shows the most efficiency of the developed approach to calculate the objective function, so that the over than 99% of deviations between PRB solution and optimum solution are less than 1.4%. Thereupon, it can be concluded that the developed PRB is so reliable and can be used as a powerful Decision Support System for decision makers.

6. Conclusions

In this paper an economic order quantity problem with stochastic parameters and decision variables has been formulated as a stochastic geometric programming model. Because of the complexity of the proposed model, specially for the practitioners such as managers, a probabilistic rule base is developed to reach the optimum or near optimum values of the decision variables and the objective function

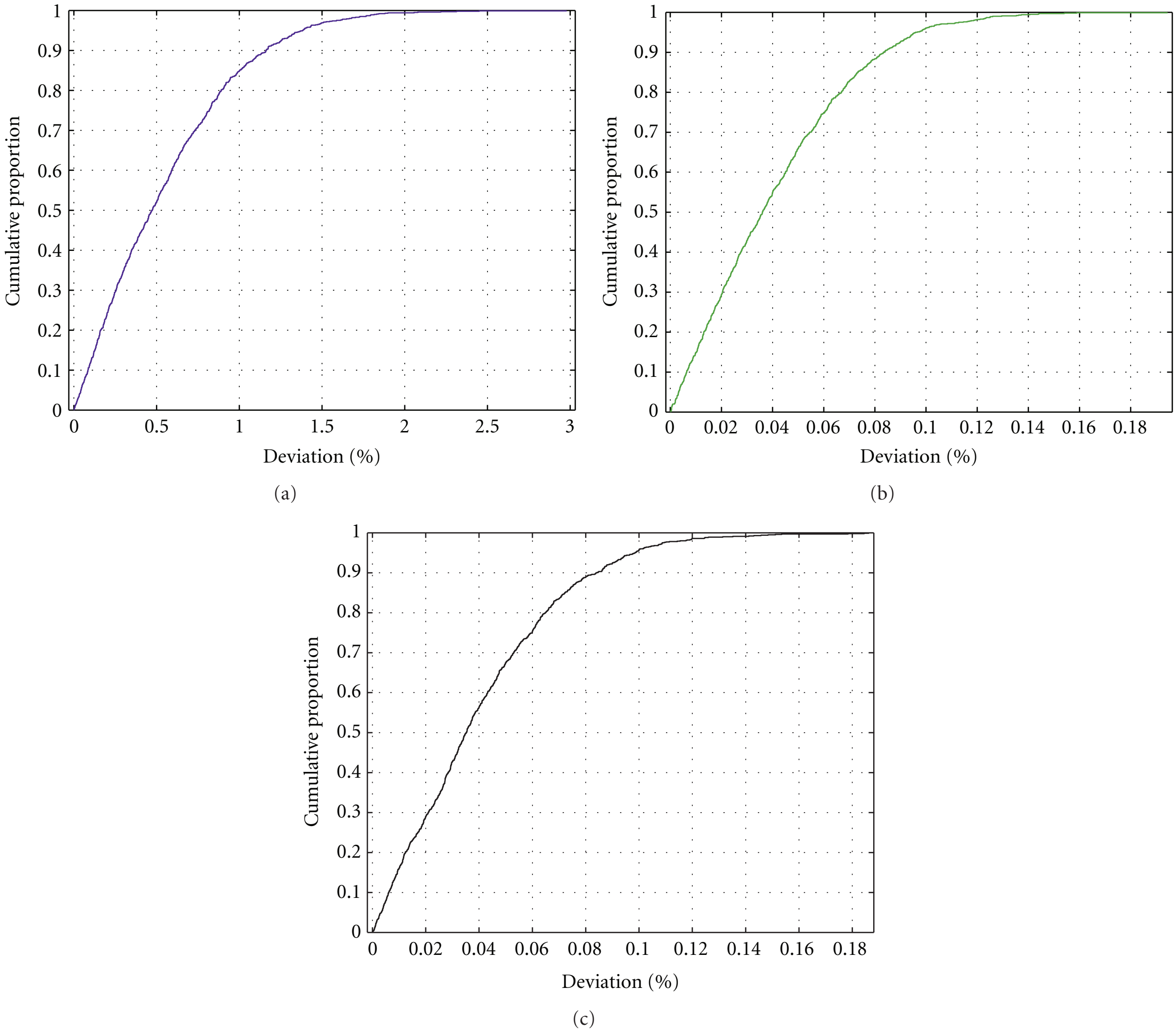

Figure 3: (a) Cumulative proportion curve of the D deviations. (b) Cumulative proportion curve of the Q deviations. (c) Cumulative proportion curve of the Z deviations, for 1,000 samples.

without solving the geometric programming model directly. More developments in this problem are possible. Interested researchers can use developed PRB to design a powerful decision support system for other applied optimization problems such as location-allocation models, portfolio investment problems, economic production quantity problems, scheduling problems, and so forth.

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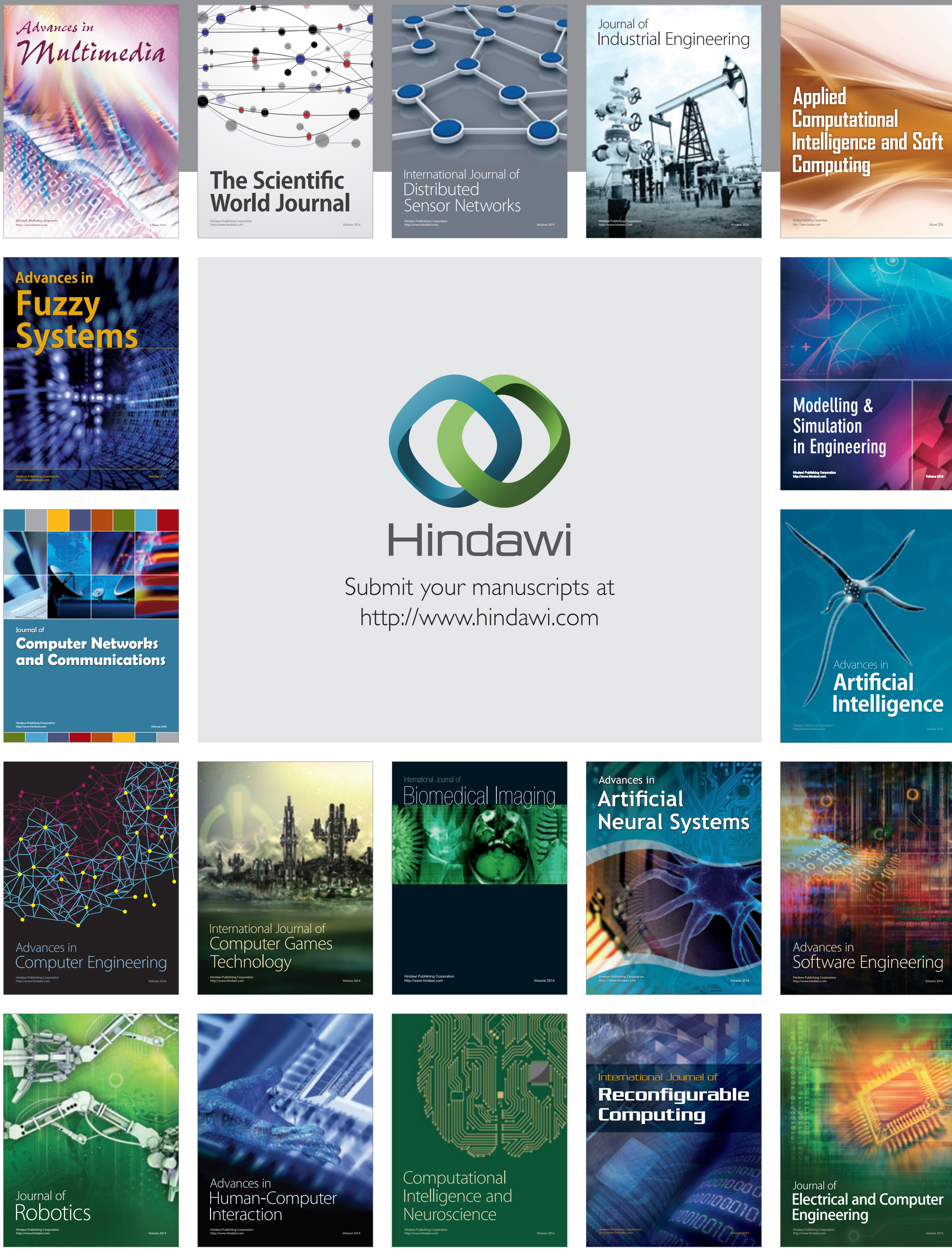
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