BIO Web of Conferences **113**, 05020 (2024) https://doi.org/10.1051/bioconf/202411305020
INTERAGROMASH 2024

Stochastic model for product supplier selection

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Abstract. The aim of the article is to develop a model of rational choice of technology and equipment supplier under conditions of external environment uncertainty. The technical and economic requirements of the customer are considered as operational, i.e. each requirement can be evaluated by expert judgement or measured using one or another means of measurement. This problem belongs to the multi-criteria ones with diverse indicators, for which traditional methods of linear convolution of criteria do not function correctly. We present a stochastic model of product supplier selection based on the concept of suitability and stochastic dominance, as well as the principle of guaranteed result in the conditions of incomplete data represented by finite limited samples of supplier characteristics. Both univariate and multivariate cases of supplier selection are addressed within the model. Ultimately, the formulated models are converted into linear Boolean programming models, which can be effectively solved using conventional linear optimization software packages.

1 Introduction

Ensuring the effective functioning of an industrial enterprise is impossible without its timely technical re-equipment through the introduction of advanced high-performance technologies and equipment. One of the main problems in the organization of technical re-equipment is the task of rational choice of technology and equipment supplier [1-2], which belongs to the class of multicriteria problems [3-4]

As a rule, the selection of suppliers of technologies and equipment for technical re-equipment of the enterprise is performed on the basis of a linear convolution model of arithmetic mean assessments of suppliers by experts, taking into account the weights of criteria of each expert of the following type:

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$$\sum_{m=1}^{e}\sum_{j=1}^{n} \propto_{im} x_{mti} \to max\,, \quad (1)$$

where e is the number of experts participating in the assessment, units;
n - number of criteria necessary for supplier evaluation, pcs;
α_{im} - weight of the i-th criterion, according to the opinion of the m-th expert, unit;
x_{mti} - score of the m-th expert of the t-th supplier on the i-th criterion, points.

It is known that linear convolution of diverse indicators is incorrect and can give erroneous final results [5].

Therefore, the authors propose a different approach for selecting a supplier of technologies and equipment for the technical re-equipment of the enterprise, based on the concept of stochastic dominance.

2 Materials and methods

The work is based on using the concept of stochastic dominance [6-10] to estimate expected utility. In this paper, linear Boolean programming methods are used [11]. In the case when distribution functions of suppliers' characteristics are unknown and cannot be determined by finite samples, and only finite limited samples of these characteristics are known, maximin (minimax) problem (see fig.1) formulations are used [12-15].

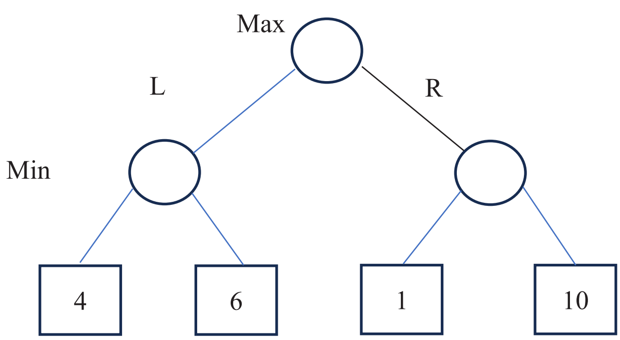

Fig. 1. Minimax algorithm

The proposed stochastic model offers a significant improvement over traditional linear convolution models by addressing the inherent limitations associated with the aggregation of diverse indicators. Stochastic dominance provides a more robust framework for evaluating supplier characteristics, particularly when dealing with incomplete or uncertain data. By prioritizing suppliers whose characteristics stochastically dominate those of other suppliers, the model ensures a higher likelihood of selecting the most suitable supplier, thereby enhancing the overall effectiveness of the technical re-equipment process.

Furthermore, the application of linear Boolean programming to the stochastic model allows for practical and efficient resolution using standard linear optimization tools. This methodological shift not only improves the accuracy of supplier selection but also aligns with the practical requirements of industrial enterprises seeking to maintain competitiveness through timely and effective technical upgrades.

In summary, the stochastic model for supplier selection presented in this study represents a significant advancement in the field of multicriteria decision-making. By incorporating concepts of suitability, stochastic dominance, and guaranteed results, the model offers a more reliable and effective approach to identifying optimal suppliers for the technical re-equipment of industrial enterprises. This innovative approach addresses the shortcomings of traditional linear convolution models and provides a practical solution that can be readily implemented using existing linear optimization software packages.

3 Results

Let a certain type of products for technical re-equipment of the enterprise can be supplied by n organizations (supplier organizations). The customer of the product makes m technical and economic requirements to the supplier of the product

$$\text{tt} = (tt_1, tt_2, \dots, tt_m)^{\text{T}},$$

where tt_j - is a deterministic quantity, $j = \overline{1,m}$;

(t is the transpose sign);

each customer requirement is operational, i.e. it can be assessed by expert judgment or measured using some means of measurement.

Let the i-th supplier is characterized by the following data:

$$dp_i = \begin{pmatrix} dp_{i11}, dp_{i12}, \dots, dp_{i1m} \\ dp_{i21}, dp_{i22}, \dots, dp_{i2m} \\ \dots \\ dp_{ik1}, dp_{ik2}, \dots, dp_{ikm} \end{pmatrix}, i = \overline{1,n}. \tag{2}$$

Here dp_i - matrix of technical and economic characteristics of the i-th supplier;

each column of the matrix is information on a specific technical and economic characteristic of the supplier, for example, data on product quality for several years (data on the number of equipment failures by year or other);

in general case the number of significant elements in the columns can be different.

The customer's task is to select the most preferable supplier based on the information I $=\{\{dp_i, i = \overline{1,n}\}$ choose the most preferable supplier.

The most preferred supplier will be the supplier whose technical and economic characteristics meet the customer's requirements and are the best.

Let's consider a "degenerate" case when the customer makes only one requirement to the supplier of products $tt_1$for example, the requirement on the efficiency of realization of certain functions. In this case in the matrix dp_i there is only one column $dp_i = (dp_{i1}, dp_{i2}, \dots, dp_{ik})^{\text{T}}$. Before making a decision on supplier selection, the data on product characteristics, represented by the column . dp_ican be considered as a sample of values of some random variable dps_i.

In this case, in order to select the preferred supplier, it is necessary to perform a stochastic comparison of the analyzed characteristics of product suppliers. The preferred supplier will be the one for which the customer's requirements will be met.

Due to the fact that characteristic data can be considered as random variables, the customer's requirement should be considered in a probabilistic sense, i.e. the condition must be met:

$$P\left(dps_j > tt_1\right) \geq P_0, \; j = \overline{1,n}, \tag{3}$$

where

$P\left(dps_j > tt_1\right) = p_{j1}$ - probability of fulfillment of one customer's requirement by the j-th supplier;

P_0 is the required probability of fulfillment of one customer requirement.

In addition to the customer's requirement determined by the ratio (3), the preferred supplier should have the maximum value of the probability of stochastic dominance of one supplier's characteristic over the characteristics of all other suppliers, i.e. the condition should be met:

$$P_j = \max_{i,j=\overline{1,n};\, i\neq j} P(\bigcap_{i=1}^{n}(dps_j > dps_i)). \tag{4}$$

Thus, for the preferred (j-th) supplier, the ratio must be satisfied:

$$j = \arg\left(P_j = \max_{i,j=\overline{1,n};\, i\neq j} P(\bigcap_{i=1}^{n}(dps_j > dps_i));\ P(dps_j > tt_1) \geq P_0;\ j = \overline{1,n}\right). \tag{5}$$

In this ratio:

$$P(\bigcap_{i=1}^{n}(dps_j > dps_i)$$

- probability of stochastic dominance of one characteristic of the *j-th* supplier over the characteristics of all other suppliers.

Assuming the events $(dps_j > dps_i), i = \overline{1,n}$ independent, we can write

$$P_j = P(\bigcap_{i=1}^{n}(dps_j > dps_i)) = \prod_{i=1}^{n} P(dps_j > dps_i) = \prod_{i=1}^{n} \pi_{ji},$$

where

$$P(dps_j > dps_i) = \pi_{ji}$$

- probability of stochastic dominance of one characteristic of the *j-th* supplier over the same characteristic of the *i-th* supplier.

Let us consider an approach to the solution of the last problem. Let the probabilities of stochastic dominance of one characteristic of the *j-th* supplier over the same characteristic of the *i-th* supplier be determined, they are represented by the following matrix P:

$$P = \begin{pmatrix} \pi_{11}, \pi_{12}, \dots, \pi_{1n} \\ \pi_{21}, \pi_{22}, \dots, \pi_{2n} \\ \dots \\ \pi_{n1}, \pi_{n2}, \dots, \pi_{nn} \end{pmatrix}. \tag{6}$$

and let the probabilities of fulfillment of one customer's requirement by the j-th supplier be determined, they are represented by a vector: $p_1 = (p_{j1}, p_{j2}, \dots, p_{jn})^{\mathrm{T}}$.

Let us define the Boolean variables $x = (x_1, x_2, \dots, x_n)^{\mathrm{T}}$; $x_j = 1$if j is defined by the relation (5) and $x_j = 0,$ otherwise. Then the problem of choosing a preferred supplier can be formulated as follows: find *j* such that $x_j = 1$ and the following conditions must be satisfied:

$$\sum_{j=1}^{n} x_j P_j \rightarrow max; \quad (7)$$

$$x_j\ p_{j1} > P_0;\ j = \overline{1,n}; \quad (8)$$

$$\sum_{j=1}^{n} x_j = 1; \quad (9)$$

$$x_j = 0; 1;\ j = \overline{1,n}. \quad (10)$$

The problem defined by relations (7) - (10) belongs to the class of linear Boolean programming problems and can be solved using typical linear optimization software packages.

The customer always has several (m) requirements for the product supplier. In this case, according to the customer's requirements, the following conditions must be met:

$$P\left(dps_{jk} > tt_k\right) \geq P_{0k},\ j = \overline{1,n}, k = \overline{1,m}, \quad (11)$$

where

$P\left(dps_{jk} > tt_k\right) = p_{jk}$ - probability of fulfillment of the k-th customer's requirement by the *j-th* supplier;

P_{0k} is the required probability of one k-th customer requirement.

In addition to the customer's requirement defined by the relation (11), the preferred supplier should have the maximum value of the probability of stochastic dominance of the characteristics of the j-th supplier over all characteristics of all other suppliers, i.e. the condition should be fulfilled:

$$P_j = \max_{i,j=\overline{1,n};\ i\neq j} P\left(\bigcap_{k=1}^{m}\bigcap_{i=1}^{n}\left(dps_{jk} > dps_{ik}\right)\right). \quad (12)$$

In this ratio:

$$P\left(\bigcap_{k=1}^{m}\bigcap_{i=1}^{n}\left(dps_{jk} > dps_{ik}\right)\right) = P_{jm}$$

- probability of stochastic dominance of *m* characteristics of the *j-th* supplier over the characteristics of all other suppliers.

Assuming the events $dps_{jk} > dps_{ik};\ i = \overline{1,n};\ k = \overline{1,m}$ independent, we can write

$$P_{jm} = P\left(\bigcap_{k=1}^{m}\bigcap_{i=1}^{n}\left(dps_{jk} > dps_{ik}\right)\right) =$$

$$= \prod_{k=1}^{m}\prod_{i=1}^{n} P\left(dps_{jk} > dps_{ik}\right) = \prod_{k=1}^{m}\prod_{i=1}^{n} \pi_{jik} = \prod_{k=1}^{m} P_{ij},$$

where

$$P(dps_{jk} > dps_{ik}) = \pi_{jik}$$

- probability of stochastic dominance of k - one characteristic of the *j-th* supplier over k - one characteristic of the *i-th* supplier.

Thus, the ratio for selecting a preferred supplier becomes more complex and is as follows:

$$j = \arg\,(P_j = max\,P(\bigcap_{k=1}^{m}\bigcap_{i=1}^{n}(dps_{jk} > dps_{ik}))\,; \qquad (13)$$
$$P(dps_{jk} > tt_k) \geq P_{0k}, \qquad j = \overline{1,n}, k = \overline{1,m}).$$

The approach to solving the problem defined by relation (13) is similar to the approach to solving the problem defined by relation (5). Let the probabilities of stochastic dominance of m characteristics of the *j-th* supplier over m characteristics of the *i-th* supplier be determined, they are represented by the following matrix P_m:

$$P_m = \begin{pmatrix} P_{11}, P_{12}, \dots, P_{1n} \\ P_{21}, P_{22}, \dots, P_{2n} \\ \dots \\ P_{n1}, P_{n2}, \dots, P_{nn} \end{pmatrix}. \qquad (14)$$

and let the probabilities of fulfillment of m customer requirements by the j-th supplier are defined, they are represented by a vector: $p_j = (p_{j1}, p_{j2}, \dots, p_{jm})^{\mathrm{T}}$.

The problem of selecting a preferred supplier can be formulated as follows: find j such that $x_j = 1$ and the following conditions must be satisfied:

$$\sum_{j=1}^{n} x_j\, P_{jm} \rightarrow max\,; \qquad (15)$$

$$x_j\ p_{ji} > P_{0i};\ j = \overline{1,n};\ i = \overline{1,m}; \qquad (16)$$

$$\sum_{j=1}^{n} x_j = 1; \qquad (17)$$

$$x_j = 0; 1;\ j = \overline{1,n}. \qquad (18)$$

In the latter relations

P_{0i} is the required probability of one i -th customer requirement;

P_{jm}- probability of stochastic dominance of m characteristics of the *j-th* supplier over the characteristics of all other suppliers.

The problem defined by relations (15) - (18) also belongs to the class of linear Boolean programming problems and can be solved using typical packages of linear optimization programs.

In the problems defined by expressions (7)-(10) and (15)-(18) it was assumed that all characteristics of the supplier are stochastic, but in many practical situations a number of characteristics can be deterministic. In this case, the following formulations of the problem of selecting a preferred supplier of products are possible.

Let the first m_1 of m data characterizing the supplier of products be considered as random variables (some sample), and the next m_2 - as deterministic variables, then the probability of stochastic dominance of m characteristics of the *j-th* supplier over the characteristics of all other suppliers is determined by the ratio:

$$P_{jm} = \prod_{k=1}^{m_1} P_{ij} \prod_{k=m_1+1}^{m} P_{ij}, \qquad (19)$$

where

for $k = \overline{1, m_1}$ the probability of stochastic dominance of m_1 characteristics of the *j-th* supplier over the characteristics of all other suppliers is determined, as before, by the ratio:

$$P_{jm} = \prod_{k=1}^{m_1} P_{ij} = P(\bigcap_{k=1}^{m_1} \bigcap_{i=1}^{n} (dps_{jk} > dps_{ik})).$$

For $k = \overline{m_{1,} m}$ the probability of stochastic dominance of m_2 characteristics of the *j-th* supplier over the characteristics of all other suppliers is defined as follows:

$P_{jm} = 1$, if for all k the following condition is satisfied: $dps_{jk} > dps_{ik}$;

$P_{jm} = 0$, if at least one k does not satisfy the condition: $dps_{jk} > dps_{ik}$

A similar situation arises with the fulfillment of customer requirements. For m_1 customer requirements we use the following ratio:

$$p_{jk} = P(dps_{jk} > tt_k) \geq P_{0k},\ j = \overline{1, n}, k = \overline{1, m_1}.$$

For $k = \overline{m_{1,} m}$ probability p_{jk} is defined as follows:

$p_{jk} = 1$, if for all k the following condition is satisfied: $dps_{jk} > dps_{ik}$;

$p_{jk} = 0$, if at least one k does not satisfy the condition: $dps_{jk} > dps_{ik}$.

Further, the problem of selecting a preferred supplier can be formulated similarly to the problem (15) - (18).

In the considered problems of selecting a preferred supplier of products, it was assumed that all probabilistic characteristics are either known or can be determined. However, in a real situation distribution functions of supplier characteristics are unknown and cannot be determined from finite samples, usually only finite limited samples of these characteristics are known. In this case, the problems of selecting a preferred supplier should be formulated as maximin (minimax) problems [16].

Consider the problem defined by relations (7) - (10). Let each column of the matrix is information about a specific technical and economic characteristic of the supplier is a sample from some unknown distribution $F_j(t)$, The problem (5) can be formulated as follows: to find a preferred (j-th) supplier, for which the following relation must be fulfilled:

$$j = \arg(P = \max_{i,j=\overline{1,n};\, i \neq j} \min_{F_{i,j}(t) \in F_{i,j0}} P(\bigcap_{i=1}^{n} (dps_j > dps_i));$$

$$\min_{F_j(t) \in F_{j0}} P(dps_j > tt_1) \geq P_0;\ j = \overline{1, n}\ ).$$

In this ratio:

$$\min_{F_{i,j}(t)\in F_{i,j0}} P(\bigcap_{i=1}^{n}\left(dps_j > dps_i\right)$$

- guaranteed probability (lower probability estimate) of stochastic dominance of one characteristic of the *j-th* supplier over the characteristics of all other suppliers, determined on the set of distributions $F_{j0}$from which samples of supplier characteristics could be obtained;

$$\min_{F_j(t)\in F_{j0}} P\left(dps_j > tt_1\right)$$

- guaranteed probability (lower estimate of probability) of fulfillment of customer's requirements, determined on the set of distributions $F_{j0}$from which samples of supplier characteristics could be obtained.

To find the guaranteed estimates, the approaches described in the authors' work [17, 9] can be used.

Then the problem of determining the preferred supplier is formulated similarly to the problem (7) - (10).

4 Discussion

Further direction of research is the development of methodological tools for determining the probability of stochastic dominance of some random characteristics over other random characteristics. One of the possible approaches to solving this problem is described in the authors' article. However, this sub-method is limited, and only with two sample moments of random characteristics obtained analytical results, it is necessary to generalize them to a larger number of sample moments. This is the most promising direction for further research.

5 Conclusions

By addressing both univariate and multivariate cases, our approach offers a robust framework for making informed supplier selection decisions in the presence of incomplete or uncertain data.

The proposed model operates under the premise that the optimal supplier is one whose attributes align closely with the technical and economic criteria set forth by the customer. This alignment is quantified through a probabilistic lens, whereby the probability of a supplier's characteristics outperforming those of its competitors is maximized. This probabilistic approach is particularly advantageous in real-world scenarios where the exact distribution of supplier characteristics may be unknown or difficult to ascertain, thereby necessitating a model that can operate effectively under conditions of uncertainty.

For the univariate case, the model simplifies the supplier selection process by focusing on a single characteristic or criterion that is deemed most critical by the customer. This might include factors such as cost efficiency, delivery reliability, or product quality. The selection process involves evaluating the probability that a supplier's performance on this single criterion stochastically dominates that of other suppliers. By maximizing this probability, the model ensures that the chosen supplier is the best available option according to the most important attribute.

In more complex scenarios where multiple characteristics must be considered simultaneously, the multivariate model provides a more holistic approach. Here, the model evaluates a set of characteristics that collectively define the suitability of a supplier. These characteristics might include a combination of cost, quality, delivery times, and other relevant performance metrics. The multivariate model extends the univariate approach by considering the joint probability of stochastic dominance across all selected characteristics. This ensures that the chosen supplier excels not just in one area, but across a spectrum of important criteria, thus providing a more balanced and comprehensive assessment.

The methodological framework underpinning our model involves the use of linear Boolean programming. This allows for the practical application of the model using standard optimization software, facilitating its implementation in real-world decision-making processes. By translating the stochastic dominance problem into a format that can be solved using existing computational tools, we bridge the gap between theoretical model development and practical application.

The implications of our model extend beyond the theoretical to the practical realm, offering a robust tool for enterprises seeking to optimize their supplier selection processes. In an industrial context, where timely and efficient technical re-equipment is critical to maintaining competitiveness, our model provides a rigorous and reliable means of selecting suppliers who are most likely to meet and exceed customer expectations. This is particularly valuable in industries where the consequences of supplier underperformance can be significant, including manufacturing, aerospace, and high-tech sectors.

The practical applications of the stochastic model for product supplier selection, as detailed in the above text, extend significantly into the domain of economics, particularly in the realms of industrial procurement, supply chain management, and strategic resource allocation. By employing a probabilistic framework that integrates the principles of suitability and stochastic dominance, this model provides a robust mechanism for optimizing supplier selection, which is a critical aspect of economic efficiency and competitive advantage in various industries.

In the context of industrial procurement, the model facilitates the identification of suppliers whose technical and economic characteristics align closely with the requirements of the enterprise. This alignment is not merely based on deterministic criteria but is evaluated through the lens of stochastic dominance, thereby ensuring that the selected suppliers are not only capable of meeting the specified requirements but also have a higher likelihood of outperforming their competitors across multiple dimensions. This probabilistic approach mitigates the risks associated with supplier underperformance and enhances the reliability of the procurement process.

Furthermore, the model's applicability extends to supply chain management, where the selection of reliable and high-performing suppliers is paramount. By maximizing the probability of selecting suppliers whose characteristics stochastically dominate those of others, the model contributes to the stability and resilience of the supply chain. This is particularly crucial in industries where supply chain disruptions can have significant economic repercussions, such as in manufacturing, pharmaceuticals, and technology sectors. The model's ability to handle incomplete data and operate under conditions of uncertainty makes it a valuable tool for supply chain managers who must navigate complex and dynamic market environments.

Strategically, the model aids in resource allocation by ensuring that investments in supplier relationships yield the highest possible returns. By focusing on suppliers who are statistically more likely to deliver superior performance, enterprises can allocate their resources more effectively, reducing wastage and enhancing overall productivity. This is particularly relevant in scenarios where resources are scarce, and the cost of supplier failures is high. The model's integration with linear Boolean programming allows for practical implementation using existing optimization software, further streamlining the decision-making process.

Additionally, the model's emphasis on both univariate and multivariate cases broadens its applicability across different sectors and types of procurement. In industries where a single criterion, such as cost efficiency or delivery reliability, is paramount, the univariate model provides a straightforward and effective selection mechanism. Conversely, in sectors where multiple performance metrics must be considered, the multivariate model offers a comprehensive assessment framework that accounts for the interplay between various supplier characteristics.

From an economic perspective, the adoption of this stochastic model can lead to significant cost savings and efficiency gains. By optimizing supplier selection, enterprises can reduce procurement costs, minimize the risk of supply chain disruptions, and improve the quality of their outputs. These benefits translate into enhanced competitiveness and market positioning, as enterprises are better equipped to deliver value to their customers while maintaining operational efficiency.

Moreover, the model's probabilistic foundation aligns with the increasing emphasis on data-driven decision-making in economics. As enterprises collect and analyze vast amounts of data, the ability to incorporate this data into supplier selection processes using advanced probabilistic techniques becomes increasingly valuable. The model's capability to handle incomplete data sets and operate under uncertainty further enhances its relevance in today's data-rich but often unpredictable economic landscape.

In conclusion, the practical applications of the stochastic model for product supplier selection in economics are manifold and far-reaching. By providing a rigorous, probabilistic framework for supplier evaluation and selection, the model enhances procurement efficiency, supply chain stability, and strategic resource allocation. Its applicability across different sectors and its integration with linear optimization tools make it a versatile and powerful tool for economic decision-making, ultimately contributing to improved economic performance and competitiveness in a variety of industrial contexts.

Future research could expand on this model by incorporating more sophisticated probabilistic techniques and exploring its application in various industrial contexts. Additionally, integrating real-time data analytics and machine learning could enhance the model's predictive accuracy and adaptability to changing market conditions. By continually refining and expanding the model, we can ensure that it remains a cutting-edge tool for supplier selection in an increasingly complex and dynamic business environment.

In summary, this paper presents a novel stochastic model for product supplier selection that leverages the principles of suitability and stochastic dominance. By addressing both univariate and multivariate cases, and translating the problem into a format solvable by linear Boolean programming, the model provides a practical and effective tool for enterprises. This approach ensures that the selected supplier not only meets the customer's requirements but also maximizes the likelihood of outperforming competitors, thereby contributing to the overall efficiency and success of the enterprise's operations.

The stochastic model for product supplier selection, as elucidated in the above text, holds significant potential for applications in predicting and preventing emergencies, particularly within the domains of supply chain management, industrial safety, and disaster preparedness. The model's foundation in probabilistic analysis and stochastic dominance provides a robust framework for anticipating potential failures and optimizing decision-making processes to mitigate the risk of emergencies.

In supply chain management, the stochastic model can be instrumental in identifying suppliers who are not only reliable under normal operating conditions but also resilient in the face of unexpected disruptions. By evaluating the probability of stochastic dominance of supplier characteristics, the model enables supply chain managers to select suppliers who are statistically more likely to maintain performance standards during crises, such as natural disasters, geopolitical instability, or sudden market shifts. This proactive approach to supplier selection helps in building a resilient supply chain that can adapt to and recover from emergencies more efficiently, thereby minimizing the economic impact of such disruptions.

Moreover, in the context of industrial safety, the model can be applied to assess and select equipment and technology suppliers based on their safety records and reliability metrics. By incorporating probabilistic assessments of supplier performance, the model allows for the identification of suppliers whose products have a higher likelihood of meeting stringent safety standards and performing reliably under stress conditions. This is particularly crucial in industries such as aerospace, pharmaceuticals, and chemical manufacturing, where equipment failures can lead to catastrophic emergencies. By ensuring that selected suppliers have a proven track record of safety and reliability, the model contributes to the prevention of industrial accidents and enhances overall operational safety.

Additionally, the model's application extends to disaster preparedness and risk management. In scenarios where emergency response equipment and services are critical, such as in healthcare, firefighting, and public safety, the model can be utilized to select suppliers whose products and services are most likely to perform effectively under emergency conditions. By evaluating the probabilistic dominance of suppliers' characteristics, emergency management agencies can ensure that they are equipped with the best possible resources to respond to crises. This proactive selection process enhances the readiness and effectiveness of emergency response efforts, ultimately saving lives and reducing the impact of disasters.

The model's emphasis on handling incomplete data and operating under conditions of uncertainty is particularly relevant for predicting and preventing emergencies. In real-world situations, data on supplier performance and reliability is often incomplete or uncertain. The stochastic model's ability to function effectively in such environments ensures that decision-makers can still make informed choices, even with limited information. This capability is crucial for emergency preparedness, where timely and accurate decision-making can significantly influence the outcome of a crisis.

Furthermore, the model's integration with linear Boolean programming allows for the practical implementation of these probabilistic assessments using existing optimization software. This means that organizations can readily incorporate the model into their existing decision-making frameworks, facilitating the widespread adoption of a probabilistic approach to supplier selection and emergency preparedness. By leveraging this model, organizations can systematically enhance their resilience to emergencies through better supplier selection and risk management practices.

In summary, the practical applications of the stochastic model for product supplier selection extend significantly into the realm of predicting and preventing emergencies. By providing a probabilistic framework for evaluating supplier reliability and resilience, the model enhances supply chain robustness, industrial safety, and disaster preparedness. Its ability to operate under conditions of uncertainty and its compatibility with existing optimization tools make it a valuable asset for organizations aiming to mitigate the risk of emergencies and improve their overall resilience to crises.

References

1. Katarzyna Grondys, Procedia Economics and Finance, **27,** 85-92 (2015) doi: 10.1016/S2212-5671(15)00976-4
2. Marcelo M. Azambuja, William J. O'Brien, Automation in Construction, **22,** 587-596 (2012) doi: 10.1016/j.autcon.2011.12.004
3. Assellaou, Hanane et al, The Journal of Engineering Research, **4,** 218-222 (2015)

4. Pravin Katakar et al, International Journal of Production Research, **51 (5)**, 1535-1548 (2013) doi: 10.1080/00207543.2012.709644
5. Richard Edgar Hodgett, The International Journal of Advanced Manufacturing Technology, **85,** 1145–1157 (2016) doi: 10.1007/s00170-015-7993-2
6. Markku Kallio, Nasim Dehghan Hardoroudi, European Journal of Operational Research, **276 (2)**, 790-794 (2019) doi: 10.1016/j.ejor.2018.12.014
7. Mikhail Lomakin et al, International Journal for Quality Research, **1,** 823-834 (2020) doi:10.24874/IJQR14.01-10
8. Thierry Post, Miloš Kopa, European Journal of Operational Research, **230 (2)**, 321-332 (2013) doi: 10.1016/j.ejor.2013.04.015
9. Mikhail Lomakin, Alexander Dokukin, Scientific and Technical Journal of Information Technologies, Mechanics and Optics, **23(3)**, 646–651 (2023) doi: 10.17586/2226-1494-2023-23-3-646-651
10. Alexei Buryi et al., International Journal for Quality Research, **15(2)**, 619-636 (2021).
11. Benedek Nagy, Acta Polytechnica Hungarica, **16 (4)**, 231-248 (2019) doi: 10.12700/aph.16.4.2019.4.12
12. Behrouz Emamizadeh, Jyotshana V. Prajapat, Optimization Letters, **5**, 647–664 (2011) doi: 10.1007/s11590-010-0230-x
13. Ashour Ibrahim, et al, 2020 IEEE International Conference on Fuzzy Systems (FUZZ-IEEE), **1-7**, (2020), doi: 10.1109/FUZZ48607.2020.9177681.
14. Peter Bühlmann, Nicolai Meinshausen, Proceedings of the IEEE, **104 (1)**, 126-135 (2016) doi: 10.1109/JPROC.2015.2494161.
15. Nicolai Meinshausen, Peter Bühlmann, Ann. Statist. **43(4)**, 1801-1830 (2015). doi: 10.1214/15-AOS1325
16. Azlan Zain et al. IOP Conference Series: Materials Science and Engineering. **864**. (2020). doi: 10.1088/1757-899X/864/1/012090.
17. Mikhail Lomakin et al., Cosmic Research, **59(3),** 199-203 (2021). doi: 10.1134/S0010952521030072