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Financial Risk Management Prediction of Mining and Industrial Projects using Combination of Artificial Intelligence and Simulation Methods

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Abstract

Feasibility studies of mining and industrial investment projects are usually associated with uncertain parameters; hence, these investigations rely on prediction. In these particular conditions, simulation and modelling techniques remain the most significant approaches to reduce the decision risk. Since several uncertain parameters are incorporated in the modelling process, distribution functions are employed to explain the parameters. However, due to the usual constrain of limited data, these functions cannot significantly explain the variation of those uncertain parameters. Support vector machine, one of the efficient techniques of artificial intelligence, provides the appropriate results in the classification and regression tasks. The principal aims of this research work are to integrate the simulation and artificial intelligence methods to manage the risk prediction of an economic system under uncertain conditions. The financial process of the Halichal mine in the Mazandaran province, Iran, is considered a case study to prove the performance of the support vector machine technique. The results show that integrating the simulation and support vector machine techniques can provide more realistic results, especially when including uncertain parameters. The correlation between the net present value obtained from the simulation and the net present value is about 0.96, which shows the capability of artificial intelligence methods and the simulation process. The root mean square error of the support vector machine prediction is about 0.322, which indicates a low error rate in the net present value estimation. The values of these errors prove that this method has a high accuracy and performance for predicting a net present value in the Halichal granite mine.

1. Introduction

In the feasibility studies of the mining and industrial projects dealing with constraints of time and resources and considering the changes in environmental conditions, the most optimum decision should be made. It can be made in either deterministic or probabilistic conditions that exist approaches to analyse and decide in each circumstance [1]. In the feasibility studies of the mining and industrial projects, the engineering economy techniques are used to predict the entire cost and profit of each investment. Hence, one of the decisions of management is to decide whether to invest in projects or develop a system. In this regard, determining the least risky project for investment is one of the significant management challenges faced with various conditions [2]. Determining a project, with a higher return on investment in the future and in a shorter time, requires expertise, prediction, and experience. Since a feasibility study usually contains uncertain parameters, the estimation requires to consider their variation [2, 3]. Simulation is one of the most remarkable methods of modelling future changes in any economic system. Simulation examines the behaviour of the uncertain parameters of the model, considering the specific distribution functions for them [2]. However, due to the limited number of data used for preparing the cash flow table of

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mining and industrial projects, the distribution function cannot perfectly describe the behaviour of the uncertain parameters, and the modelling accuracy considerably decreases [4].

In the recent decade, non-linear data-driven models have been widely applied to solve problems. These methods can control the behaviour of fundamental physical or other processes. These techniques may be deduced from dependable predicting models using the previous data of projects. These modelling tools, such as artificial neural networks (ANNs) do not need knowledge of the mathematical relationships between the inputs and related outputs, obvious characterization, conditions, and quantification of physical properties. Artificial intelligence techniques have successfully been used in many different applications because of their ability to recognize the possible complexities between input and output included in a system. Research has shown that ANN and support vector machine (SVM) have the best performance in predicting the mining capital cost and the highest R^2 to use the predictions [5]. Many researchers found that the SVM and Wavelet-based forecasting had the best prediction capabilities among non-linear forecasting methods [6]. Behzad *et al.* [4] compared the ANN and SVM techniques and proved that both approaches were data-driven models, and the SVM method makes the running time considerably quicker, with the same or higher accuracy. SVM is one of the appropriate networks, used successfully to predict problems of non-linear systems [4, 7]. Artificial intelligence models usually lead to more satisfactory results than classical regression equations due to low error and high correlation coefficient [8]. Osuna *et al.* [9] introduced an entirely new family of SVM training methods. The theorem of Osuna *et al.* [9] showed that the whole SVM training problem was separated into several smaller sub-problems. Then each sub-problem is optimized, minimizing the original quadratic programming problem. Today, the sequential minimal optimization algorithm (SMO) is used as an example of the theorem of Osuna *et al.* [9] in operation [10, 11].

With increasing and growing natural resources, the optimal use of these resources is felt more in the construction industry. In line with the implementation of this philosophy, optimization techniques in the concrete mix are evaluated to improve the main parameters of resistance and fracture toughness [12-17], whereas a major part of civil and mining structures deals with rock seams and cracks, machine learning has been evaluated in determining permeability to describe hydrocarbon reservoirs [18]. In estimating the pores, considering the model complexity in hydrocarbon reservoirs, SVM has shown many capabilities [19]. It is used in predicting rock fracture toughness, which is influenced by the main rock parameters including uniaxial compressive strength, tensile strength, and rock modulus [20]. Also due to the complexities in rock masses to determine the discharge characteristics, considering rock discontinuities in determining the classification of an aquifer, the performance and high accuracy of the SVM is evaluated [21]. In exploratory studies, to determine the alteration classification of an area [22] and in exploratory geochemical spectroscopy in lead and zinc alluvial sediments, the results of SVM have the highest accuracy and performance [23]. Also this technique has predicted the damage caused by blast vibrations with high accuracy [24].

The results have shown that this machine can be treated as a generalized and high-performance method to predict data containing considerable noise [25, 26]. This research work aims to integrate the simulation and SVM techniques for risk management and predicting the future of economic systems under uncertain conditions. Also, the financial process of the Halichal granite mine in the Mazandaran province and its economic future was simulated and predicted to analyse the risk.

2. Materials and Methods

2.1. Project description

In this work, the Halichal granite mine in the Mazandaran province (northern Iran) is considered a case study. In this area, most outcrops are sedimentary units of the Shemshak formation. Intrusive units in the sill form with a thickness of 100 m and a length of 400 m have a protrusion in the mine region, which has contact with the host rock. The oldest and most abundant rocks are Shemshak formation deposits, mainly shale, sandstone, and sometimes siltstone. These deposits extend roughly from east to west. In this studied area, the plutonic intrusion includes black needle crystals of amphibole in a transparent matrix of quartz and feldspar (plagioclase) (Figure 1). Due to its proximity to the Shemshak formation of Jurassic, this mass belongs to the cretaceous plutonic intrusions. It has a granular buffer named alkali syenite based on kaolinized amphibole. The potential and definitive reserves of the mine are estimated at 1.1 million tons and 556,000 tons, respectively.

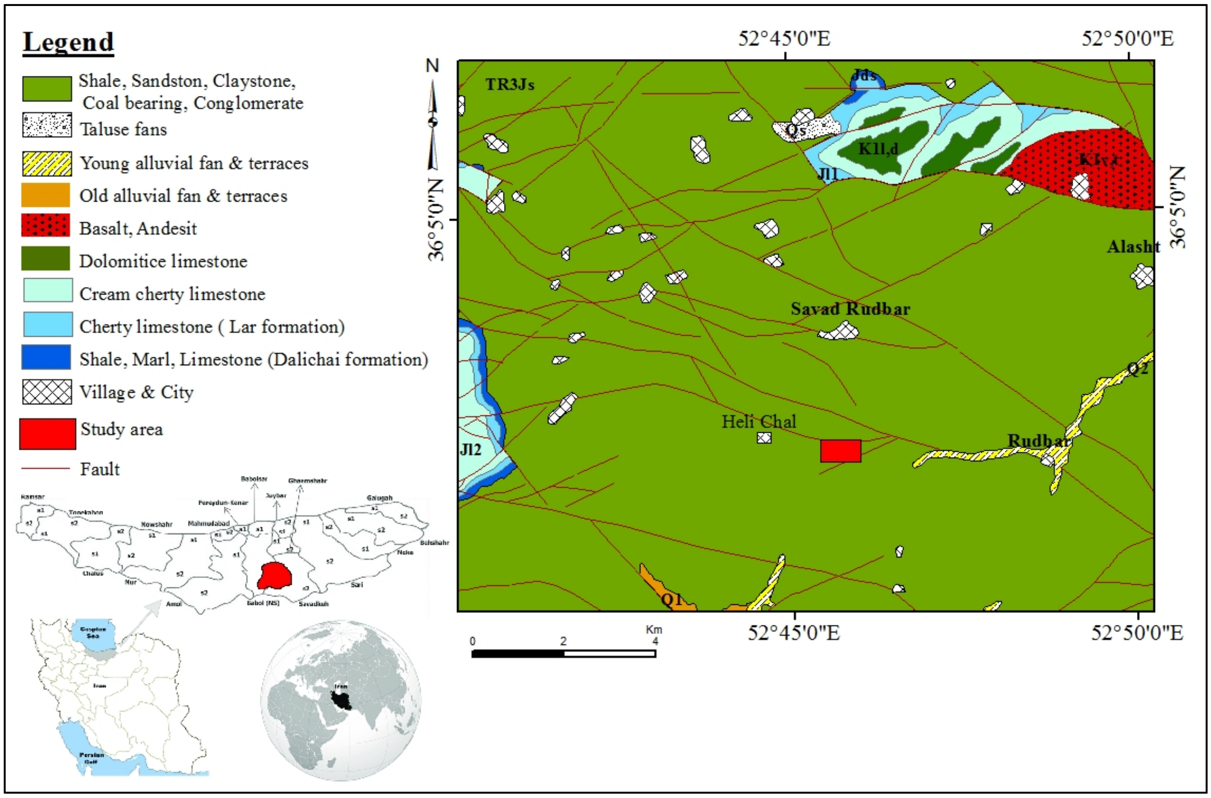

Figure 1. Geology map of the studied area.

2.2. Support vector machine

The SVM algorithm in pattern recognition builds non-linear decision-making functions via a classifier that can categorize data in a higher space. For generalizing the SVM algorithm to the regression estimates, a similar margin in the space of objective values (y) is created by Vapnik's ε-insensitive loss function, as Equation (1),

$$|y - f(x)|_\varepsilon := \max\{0, |y - f(x)| - \varepsilon\} \quad (1)$$

Given the mentioned conditions, Equation (2) is used to estimate a linear regression,

$$f(x) = (w.x) + b \quad (2)$$

where f(x) is a linear function, w is the weight vector, and b is the bias. Considering the accuracy and error of the model can be written Equation (3),

$$\frac{1}{2}\|w\|^2 + C\sum_{i=1}^{m}|y - f(x)|_\varepsilon \quad (3)$$

and given the constraints of the problem, the convex constrained quadratic optimization problem can be written as Equation (4) [27, 28, 29, 30, 31]:

$$L(w,\xi,\xi') = \frac{1}{2}\|w\|^2 + C\sum_{i=1}^{N}(\xi_i + \xi_i')$$

$$Subject\ to\ \begin{cases} y_i - w^T.x - b \le \xi_i + \varepsilon \\ w^T.x + b - y_i \le \xi_i' + \varepsilon \\ \xi_i, \xi_i', x_i \ge 0 \end{cases} \quad (4)$$

where ξ_i and ξ_i' are slack variables introduced to satisfy the constraints on the function. Hence, support vector regression (SVR) fits a function to the given data by minimizing the training error and penalizing complex fitting functions. The first term of Equation (4) is the Vapnik-Chervonenkis (VC) confidence interval, whereas the second term is the empirical risk. Both terms restrict the upper bound of the generalization error rather than limiting the training error. It means that SVR strikes a balance between the experimental error and VC-confidence interval, which leads to an improved generalization performance, better than the neural network models [32]. In Equation (4), C ensures that the margin ε is maximized and the error of classification ξ is minimized. These equations are set for all i = 1, …, m. According to Equation (4), any error less than ε does not require a non-zero ξ_i

or ξ_i', and does not fit into the objective function [28, 29, 30, 31, 33]. Considering the Lagrange function to solve the above optimization problem, Equation 4 becomes Equation 5. In this case, the function of Equation 5 to be maximized,

$$L(\alpha,\alpha') = \frac{1}{2}\sum_{i=1}^{N}\sum_{j=1}^{N}(\alpha_i - \alpha_i')x_i^t x_j(\alpha_i - \alpha_i') + \sum_{i=1}^{N}((\alpha_i - \alpha_i')y_i - (\alpha_i + \alpha_i')\varepsilon) \quad (5)$$

$$\text{Subject to } 0 \le (\alpha_i - \alpha_i') \le C \quad (6)$$

where α and α' are Lagrange multipliers. In this case, x_i appears only in the process of internal multiplication. To better represent the data, can move it to a higher space known as the feature space (Hilbert space), in which case Equation 7 is shifted:

$$x_i.x_j \to \varphi(x_i).\varphi(x_j) \quad (7)$$

In these conditions, the $\varphi(x_i)$ value is well-represented by employing an appropriate kernel that classifies the data in the upper space, while the input space is still non-linear. Therefore, inseparable data in the input space is detached in the Hilbert space through an appropriate kernel such as the Gaussian kernel (radial basis function). This kernel is provided as Equation 8:

$$k(x_i, x_j) = e^{-\|x_i - x_j\|^2/2\sigma^2} \quad (8)$$

Based on the above conditions, the regression estimate will be expressed as Equation 9:

$$y_i = \sum_{i=1}^{N}\sum_{j=1}^{N}(\alpha_i - \alpha_i')\varphi(x_i)^T\varphi(x_j) + b = \sum_{i=1}^{N}\sum_{j=1}^{N}(\alpha_i - \alpha_i')K(x_i, x_j) + b \quad (9)$$

where b is calculated considering Equation 4.

$$\xi_i = 0 \text{ if } 0 < a_i < C$$

$$\xi_i' = 0 \text{ if } 0 < a_i' < C$$

Equation 9 is the basis of SVM in the data forecasting process [27, 34-38].

SVM has been employed for estimating the regression to solve the economic systems in which the actual value functions are evaluated. In this case, it is called support vector regression (SVR). The learning process in the SVR approximates objective values with minimum risk based on a set of input-output data. SVR performs this approximation using an estimation function and ε-Insensitive loss function to decrease scattering for SVR [28, 33]. The estimation function is initially linear [31, 39].

The goal of ε-SVR is to produce an estimation function f(x) for the output variables, using deviations in the actual training data. The complexity of f(x) depends on the ε-values; the higher the ε-values, the tighter the approximating models and vice versa. Smaller ε-values penalize a larger portion of the training data [29, 40]; thus, the choice of ε-values is evaluative for generalizing the regression models. f(x) is found by minimizing the regulated risk functional [30-32, 41].

In summary, to achieve a lower risk, it is required to concurrently modify the complexity of the model and the training data error that causes lower the regulated risk functional. This idea improves the generalization of the SVR; thus it produces the estimation function using the given data by parallel minimizing the training error, penalizing the complexity of the fitting functions, and limiting the upper bound of the generalization error. By balancing between the empirical error, and Vapnik-Chervonenkis confidence interval, SVR outperforms the ANN models for generalization [28, 33, 42]. Then it can map the data points into an alternative space (a pre-Hilbert or inner product space) to get a potentially better representation of the data in a nonlinear case. Thus while the problem of the data for n-parity or the two spirals is inseparable by a hyperplane, in the input space, it can be separated in the feature space by proper kernels [30, 31, 43-45].

There are several algorithms for SVM training, among which SMO has been recognized as one of the most capable algorithms [30, 46]. SMO solves the problem of quadratic programming with a lower computational cost than the other method. It utilizes [9]'s theorem to divide the overall quadratic programming problem into multiple smaller quadratic programming problems to improve convergence. There are two particular parts in the structure of an SMO: (1) a heuristic function to choose multipliers in the optimization step and (2) an analytic method to solve the two Lagrange multipliers. The advantage of an SMO lies in the analytical solution of two Lagrange multipliers. It can entirely avoid numerical quadratic programming optimization. Furthermore, using SMO to solve large SVM training problems improves the computational process by lowering memory requirement, and as a result, a higher speed [30, 47, 48].

2.3. Flowchart of analysing process

The steps of this work are according to the flowchart in Figure 2. First was plotted the frequency histogram. Then were determined the input and output parameters of the system. The training aimed to reduce the error percentage and increase the correlation. Then the best method was determined by successive repetitions during the training.

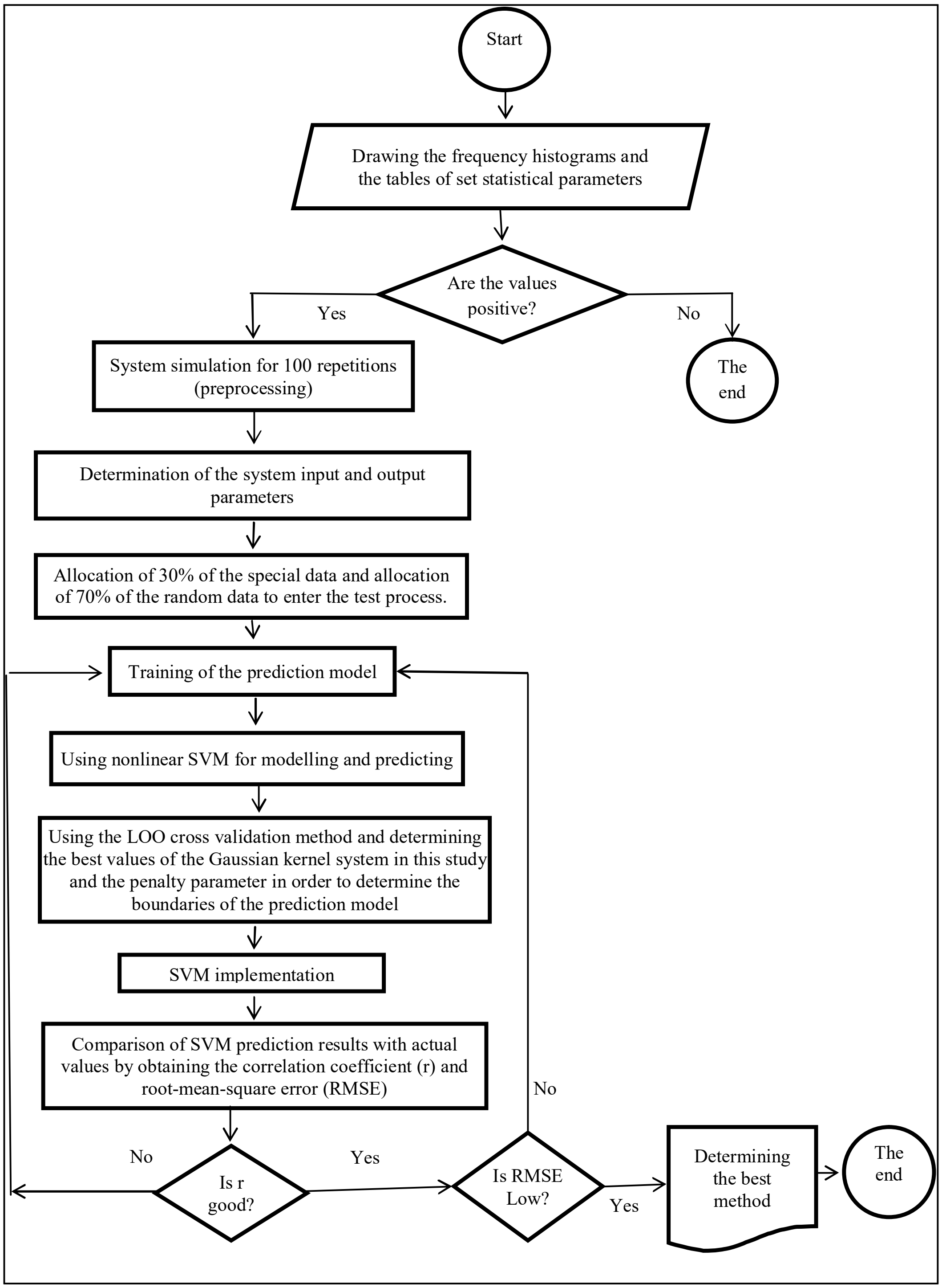

Figure 2. Flowchart of process of performing the proposed method.

2.4. Simulation and financial estimation of economic systems

Simulation is making a model based on mathematical and logical equations from an actual system. This type of modelling considers the time and variations of parameters involved in the system and studies it to achieve results about the components of the actual system [1]. In this case, the system behaviour is evaluated considering the time and variation of the parameters using a simulated model. The purpose of simulating the model is to evaluate an objective function for different values of input variables. The simulation results are shown as a range of numbers that can be considered a distribution function. The main reasons for applying the simulation can be classified into four categories: (1) Mathematical modeling is a complicated process, and cannot often be solved without sufficient assumptions, (2) Models with a random parameter can be solved with difficulty, (3) Simulation can be efficiently run via powerful software and computers, and (4) Mathematical models usually consider the system to be stable [49].

In the financial estimation of economic systems containing many uncertain parameters, simulation is the best method to estimate the behaviour of the parameter to minimize error and reduce risk. In this case, past and current information are applied to predict the future [50]. For instance, demand for future production, the return rate, and net present value (NPV) are uncertain parameters that can be described using the probability distribution function [51, 52]. Thus the uncertainty in any project variable is considered not as a constant number but as a probability distribution function in each of the cells of the financial estimate table, and risk assessment can be calculated with the expected values.

3. Results and Discussions

3.1. Financial process of Halichal granite industrial and mining unit

In the feasibility studies of the Halichal Granite mine in the definite state, according to the annual production rate, yearly costs, sales price, and other parameters involved in the financial process, the NPV and investment return rate (IRR) are calculated to compare with the simulation and prediction results. Table 1 provides the cash flow of the mine.

Table 1. Distribution of cash flow (DCF) of Halichal granite mine.

Year	Annual production (ton)	Sales value per ton	Taxable income	Inflow	Outflow	Cash flow
0	0.000	0.000	0.000	2561247.000	0.000	-2561247.000
1	50000.000	55.000	550122.000	0.000	849733.400	849733.400
2	50000.000	66.000	88454384.000	0.000	981406848.000	98140685.000
3	50000.000	79.200	1239762.000	0.000	1153241.390	1153241.400
4	50000.000	95.040	1631515.400	0.000	1369795.376	1369795.400
5	50000.000	114.048	2075760.000	0.000	1637417.991	1637418.000
6	50000.000	136.857	2589458.000	50000.000	1964383.785	1914383.800
7	50000.000	164.229	3191334.000	0.000	2361111.250	2361111.300
8	50000.000	197.075	3902640.500	0.000	2840467.581	28404676.000
9	50000.000	197.075	4747972.300	0.000	3418165.984	3418166.000
10	50000.000	283.788	5756164.100	0.000	4113265.969	4113266.000

Table 1 provides cash flow in the last row, and parameters such as the annual production, sales value, and the current yearly costs are assumed to be equal for all years. Based on the cash flow row and considering the minimum attractive rate of return (MARR), 25% of the NPV was calculated as 14704.5$. Also the investment return rate (IRR) was 31%.

3.2. Uncertain parameters of the financial process of Halichal granite mine

After analysing the parameters of the financial process of the mine, were detected the uncertain parameters, production rate, and sales price. To predict the behaviour of parameters and obtain the distribution functions of each one, available information from the past ten years was used. As seen in Table 1, plotting the frequency histogram and fitting the distribution curve for each of the variables of annual production rate and the sales price were obtained as Logistic (156.720; 67.553) and RiskBetaGeneral (0.3082; 0.083714; 0.0000; 50000), respectively. Figures 3 and 4 show these distribution functions.

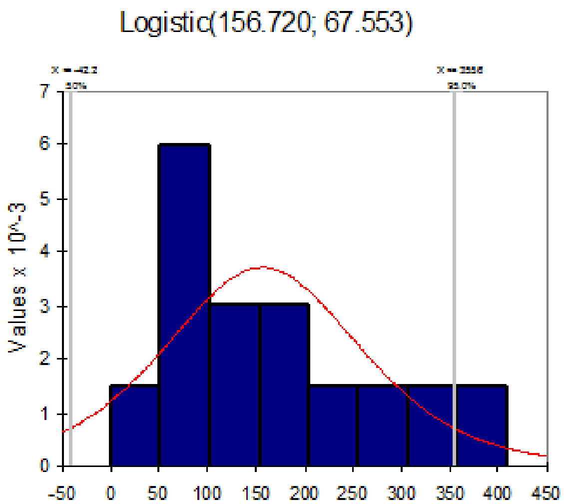

Figure 3. Distribution function of sales price.

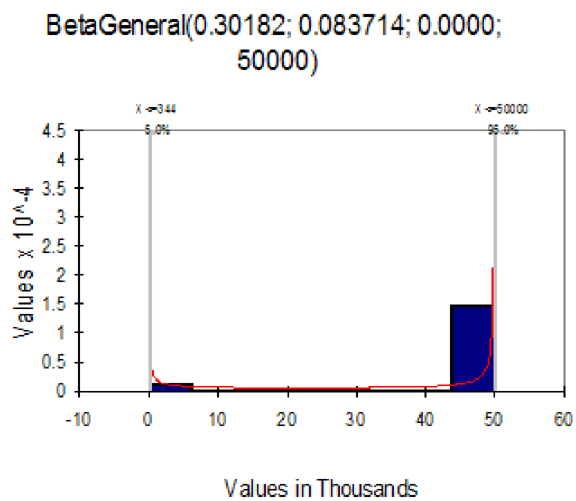

Figure 4. Distribution function of annual production.

Afterward, the resulting distribution functions were put in the DCF Table for production rate and sales price.

3.3. Financial process simulation of Halichal granite mine

For simulating and studying the changes in the NPV due to variations in the future input parameters, random numbers are generated for each of the uncertain parameters based on the obtained distribution functions. Generating random numbers enables us to assess the variability of NPV based on the inflation changes, production rate, and sales price. In this condition, at each sampling process, generating random numbers is repeated for the uncertain parameters. The cash flow table cells are correlated; thus NPV is recalculated based on the new numbers. For the financial process of the Halichal granite mine, after entering the distribution functions, first, cells with uncertainty were selected as simulation inputs. Then the characteristic cell of NPV was chosen as a simulation output. After specifying the input and output cells, 100 repetitions were considered for simulation. By performing these calculations, 100 values were obtained for NPV (due to 100 times random sampling from cells with the uncertainty using the distribution functions). Finally, due to the obtained values, was plotted the NPV histogram. Figure 5 shows the distribution histogram of NPV related to the system output, and Figure 6 provides its cumulative distribution.

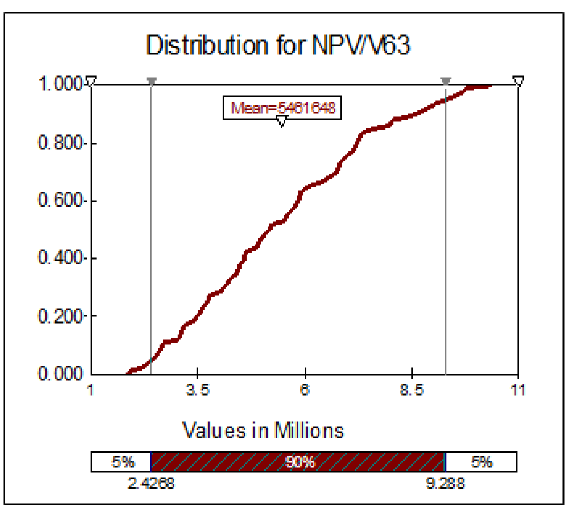

Figure 5. Distribution of NPV values.

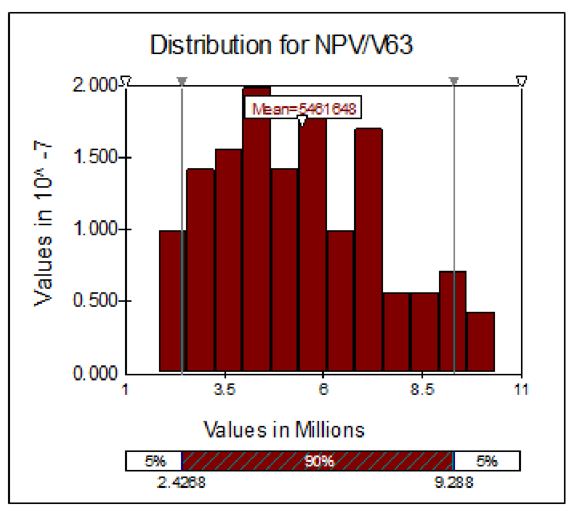

Figure 6. Cumulative distribution of NPV values.

As shown in Figures 5 and 6 can investigate the changes in the NPV to 100 times of sampling. Using plotting the frequency histogram and table of the statistical parameters for the set of iterations can be observed the percentage of times that NPV was taken for different values. Even can be assessed the times' percentage that NPV is negative. Based on these results, we can decide on project implementation or non-implementation with the necessary accuracy. According to a case study conducted in the cash flow Table of the Halichal granite mine, based on the resulting graphs and Tables, the NPV will never be negative. The system is simulated for 100 iterations (100 possible modes predicted for the future). The simulation results are sensitive to input parameters. For instance, if, in the above model, the distribution of production or cost changes, NPV may change significantly in the output. Therefore, it is necessary to be careful about the changes in inputs in a system to consider the best input distribution. According to the ten-year data of this mine, fitted distributions are the best possible fits, but not certain. Therefore, it cannot be entirely sure that NPV of the mine will never be negative. The proposed solution for solving this problem is to use the SVM to predict the NPV based on the simulated data for 100 iterations. It can partly improve the prediction process and give more confidence to investors.

3.4. SVM implementation

In this study's prediction process of NPV based on two criteria of the sales price and annual production, 100 data resulting from the simulation for the above parameters were used. It was considered NPV as the output value. Also were considered sales price and annual production as the input parameters. In this regard, 70 data was randomly assigned to the training process and 30 data to the test process. The validation process was carried out based on the leave-one-out cross-validation method because this validation type did not impose any bias on the model [47]. Since the non-linear vector machine was considered to model and predict, choosing an appropriate kernel for implementation seems necessary. Based on previous studies, the Gaussian kernel was selected as the best kernel for modelling, introduced by many researchers as the best kernel for the prediction process [31, 53]. The technique of leave-one-out validation was applied to determine the Gaussian kernel sigma parameter and the penalty parameter ε in determining the boundaries of the predicted model. Figure 7 shows the results of this study.

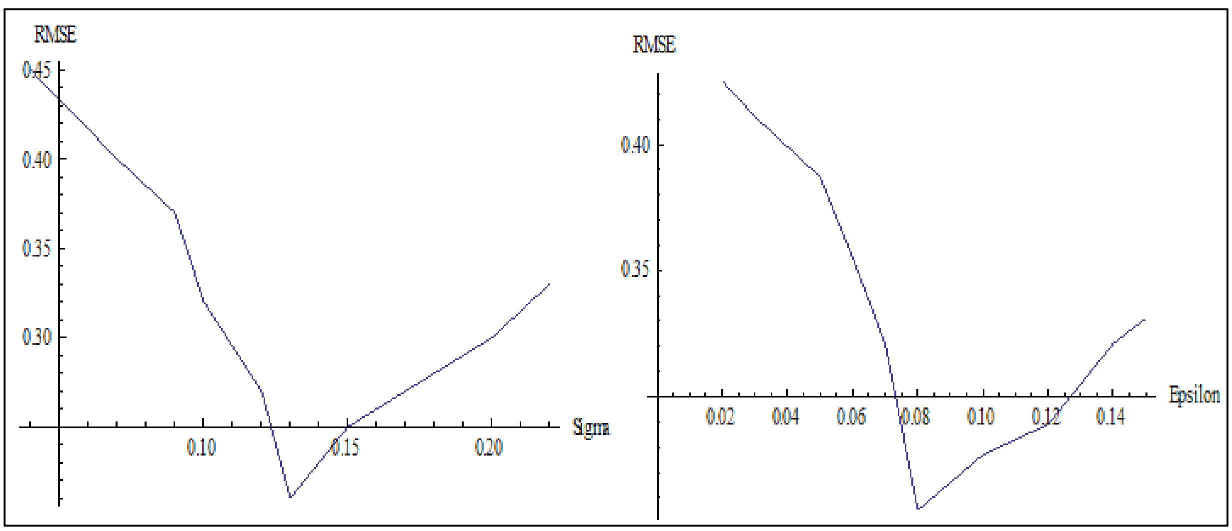

Figure 7. Different values of parameter ε against error (right) and sigma against error (left) in the leave-one-out cross-validation process of the model.

Figure 7 shows that 0.13 and 0.08 are the best values for sigma and ε, respectively. Based on the specified parameters, was carried out SVM implementation. Table 2 compares the SVM results to actual NPVs. Besides, Figures 8 and 9 show the accuracy and performance of SVM in the predicting process of NPV.

Table 2. Comparing NPV of the simulated values with the values predicted by SVM.

NPV of simulated values	Predicted net value by SVM	NPV of simulated values	Predicted net value by SVM
8872234	9072195	9454712	8754314
3096807	3496779	5805695	5514989
3090417	3390398	4421139	6720128
5909054	5409047	2320241	3420234
1033999	1133976	4933431	5944527
7323822	7643799	6765765	7231997
7956832	7656802	4284475	4595787
13024883	3264901	6778150	7498170
8032357	8452345	3144122	2531330
5658619	7658598	50532214	6263113
9601104	9521099	7257279	6560337
2426767	2626760	5221235	4221546
4901161	4651151	4435678	3735996
4084151	4454121	3593356	3093649

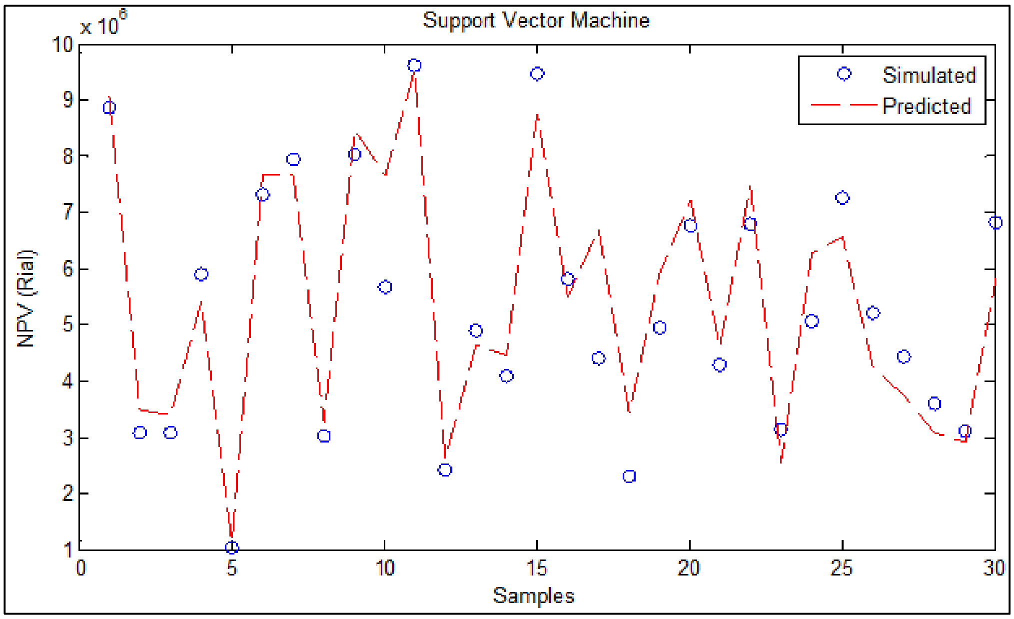

Figure 8. SVM performance in predicting the NPV of the Halichal mining and industrial plant.

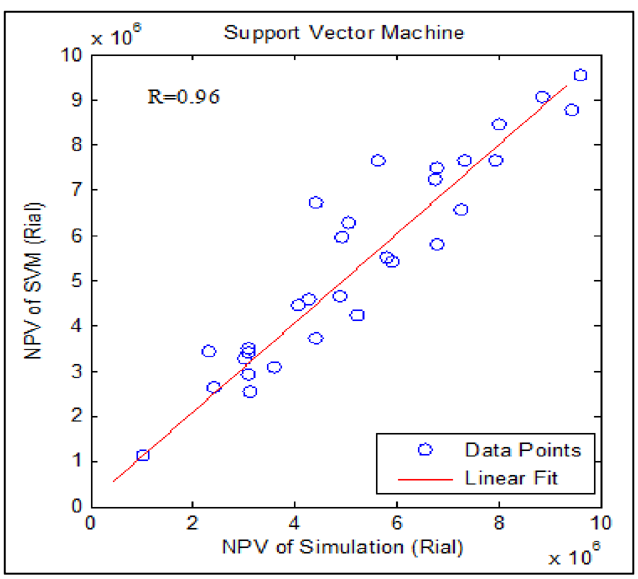

Figure 9. Correlation coefficient between the NPV values and the value predicted by SVM.

Figure 9 shows a good correlation between the NPV of the simulation and the NPV of the simulation with the SVM. The correlation coefficient between them is 0.96, which indicates the ability of SVM. Calculating the root mean square error (RMSE) of the SVM prediction was 32.2, which suggests a low error in estimating the NPV. Furthermore, SVM carried out this prediction quickly, and other ANNs such as recurrent neural networks do not commonly have this property. All the above features prove the ability of SVM to predict NPV.

4. Conclusions

SVM in decision management at different times and dealing with different situations, especially when there are several options with uncertain variables in decision-making, should be accurate enough to make the optimal decision. In this condition, is minimized the risk of the results of decision-making. In such situations, the usual solution is to use simulation methods that make it possible to manage risk and make decisions under uncertain conditions. Since these methods use a limited number of data to describe a system's behaviour, the analysis results of these approaches will not be dependable. Utilizing powerful artificial intelligence methods such as SVM with the simulation process can be reliable to decision-makers and investors. In this work, SVM and simulation methods were applied to predict the NPV of the mine. The results show that:

- Integrating these two methods better predicts NPV and decreases the project risk.
- The correlation between the net present value obtained from the simulation and the net present value is about 0.96, which shows the capability of artificial intelligence methods along with the simulation process.
- The root mean square error (RMSE) of the support vector machine prediction is about 0.322, which indicates a low error rate in net present value estimation.
- The values of the errors proved that this method was high accuracy and high performance for predicting the net present value in the Halichal granite mine.
- It is proposed to use simulation techniques and artificial intelligence in feasibility studies and financial estimation of investment and economic systems, especially under conditions that the parameters are related to the future, to maintain the dynamics of the modelled system and obtain more realistic results.

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پیش‌بینی مدیریت ریسک مالی پروژه‌های معدنی و صنعتی با استفاده از ترکیب روش‌های هوش مصنوعی و شبیه‌سازی

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چکیده:

مطالعات امکان‌سنجی پروژه‌های سرمایه‌گذاری معدنی و صنعتی معمولاً با پارامترهای غیرقطعی همراه است؛ از این رو، این تحقیقات متکی به پیش‌بینی هستند. در این شرایط خاص، تکنیک‌های شبیه‌سازی و مدل‌سازی مهم‌ترین روش‌ها برای کاهش ریسک تصمیم‌گیری هستند. به دلیل اینکه چندین پارامتر غیرقطعی در فرآیند مدل‌سازی گنجانده می‌شوند، از توابع توزیع برای توضیح پارامترها استفاده می‌شود. با این حال، به دلیل محدودیت معمول داده‌های محدود، این توابع نمی‌توانند تغییرات پارامترهای غیرقطعی را به طور قابل‌توجهی توضیح دهند. ماشین بردار پشتیبان، یکی از تکنیک‌های کارآمد هوش مصنوعی، نتایج مناسبی در طبقه‌بندی و رگرسیون ارائه می‌دهد. هدف اصلی این پژوهش ترکیب روش‌های شبیه‌سازی و هوش مصنوعی برای مدیریت پیش‌بینی ریسک یک سیستم اقتصادی در شرایط غیرقطعی است. فرآیند مالی معدن هالیچال در استان مازندران، ایران، به عنوان یک مطالعه موردی برای اثبات عملکرد تکنیک ماشین بردار پشتیبان در نظر گرفته شده است. نتایج نشان می‌دهد که ترکیب تکنیک‌های شبیه‌سازی و ماشین بردار پشتیبان می‌تواند نتایج واقعی‌تری ارائه دهد، به‌ویژه زمانی که شامل پارامترهای غیرقطعی باشند. همبستگی بین ارزش فعلی خالص به دست آمده از شبیه‌سازی و ارزش فعلی خالص حدود ۰/۹۶ است که نشان دهنده قابلیت روش‌های هوش مصنوعی و فرآیند شبیه‌سازی است. خطای مربع میانگین ریشه‌ی پیش‌بینی ماشین بردار پشتیبان حدود ۰/۳۲۲ است که نشان‌دهنده میزان خطای پایین در برآورد ارزش فعلی خالص است. مقادیر این خطاها ثابت می‌کند که این روش از دقت و کارایی بالایی برای پیش‌بینی ارزش فعلی خالص در معدن گرانیت هالیچال برخوردار است.

کلمات کلیدی: تحلیل ریسک، مدل شبیه‌سازی، اقتصاد، فرآیند مالی، ماشین بردار پشتیبان.