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Designing Multi-Objective Optimization Model of Electricity Market Portfolio for Industrial Consumptions under Uncertainty

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ABSTRACT: In deregulated electricity markets, the electricity consumer should distribute his required electricity optimally between different markets including spots markets with instantaneous price and bilateral contract markets. The present study is aimed to design a model for selecting the optimal electricity market portfolio, so the purchase costs can be minimized by considering a risk level. For this purpose, an optimization approach based on random planning was proposed to minimize costs and reduce power supply risk. Conditional value at risk was used as an appropriate and well-known factor for reducing unfavorable situations in decision-making under uncertain conditions. For simulations, the real information of Iran in 2018 was used as much as possible. Due to the small number of industrial subscribers, the whole population was studied. A genetic algorithm has been used to solve this optimization problem. In addition, MATLAB software was used for implementing the proposed model. The efficiency of the proposed model was proved by analyzing different sensitivities and the best components of the risk-averse decision-making purchasing portfolio in β=5 included from the energy exchange, then from the energy pool, and finally from bilateral contracts.

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1- INTRODUCTION

In addition to its advantages and positive points, liberalizing the electricity industry has caused some operational complexities and financial risks. In this structure, the number of market actors increases, and their relations become more complex. Furthermore, large-scale financial exchanges are formed between such actors. As a result, it can cause some risks such as price fluctuations, volume fluctuations, credit risks, and operational risks. Identifying the effects of different risks related to market actors is incredibly important in such environments. Furthermore, designing and applying some strategies to manage and eliminate such risks are greatly essential. The electricity industry has encountered fundamental changes in the world during the past two decades. Furthermore, it has been expressed under different titles such as deregulation, review of laws, or deconstruction, and so on. In the traditional structure of the electricity industry, known as systems with vertically integrated structures, a company was in charge of the production, transmission, and distribution of electricity. In the new structure, a company fails to take advantage of such an inherent monopoly, and the various parts of the electricity industry including production, transmission, and distribution are separated from each other [4].

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The electricity industry of Iran has experienced four evolutionary phases of regulation, deregulation, deconstruction, and privatization. Regulation increased the managerial and ownership role of the government in the electricity industry, while deregulation changed the laws leading to the continued presence of the government in the electricity industry and created a legal framework for the private sector. Deconstruction separated the vertical monopoly into production, transmission, and distribution. Finally, privatization transferred ownership to the private sector. Reviewing the previous studies on the Iranian electricity market showed some indicators of these risks [3]. In addition, some factors and limitations differentiate the Iranian electricity industry from other counties economically, socially, and etc. Such factors are related to the electricity system, as well as the political and cultural conditions of the country. Electricity cannot be purchased and stored for consumption. The new electricity market is highly volatile compared to the commodity market and the actors of this market are exposed to significant risks arising from volatile market conditions. This study provided a solution for the problem of optimal risk management from project portfolio management in deregulated electricity markets. Producers and buyers compete for the exchange of their required electricity in the electricity markets and offer their

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prices to the market operator at different times. Cash prices, along with high risk and changes determined in competitive markets, change the behavior of market actors. Based on one of the acts approved by the Delegation of ministers in 2015, the subscribers with a contract power of more than five MW, known as large consumers, can supply their required electricity from the energy exchange, energy pool, bilateral contracts, or their power plants. If the power plants cannot generate the committed electricity for any reason, the subscriber's electricity is supplied through the national grid, and the power plant is obliged to compensate the related costs in the electricity market based on the regulations approved by the board of market regulation.

This study aimed to present a model for large consumers to design and supply their optimal energy portfolio from the energy pool of the wholesale market, signing bilateral contracts with power plants, and energy exchange in the physical market at the minimum cost. Thus, it is assumed that the input electrical energy plays a significant role in the production process of this consumer and constitutes a considerable part of production costs. In addition, it is assumed that this consumer buys a significant portion of demand from the pool and energy exchange. Due to uncertainty in electricity prices, the final goal of large consumers is to minimize the expected cost of electricity supply with the risk related to price changes, which is an issue of electricity supply for large consumers. Furthermore, risk means that the fluctuations related to electricity supply cost significantly increase the risk of imposing a cost level. Uncertainty is considered only in the instantaneous prices of the energy pool and energy exchange. The future prices of electricity purchase contracts are fixed and risk-free and are considered as coverage for risk [1].

2- REVIEW OF LITERATURE

The previous studies mostly focused on the electrical energy sales portfolio. However, few studies are available on purchasing the optimal electrical energy portfolio from the consumer perspective [7]- [9]- [10]- [11]- [12]- [29]. Zare et al., presented a method for determining the strategy of large consumers supplying their electricity demand from the market. In this study, they used the information gap decision theory for modeling the cost uncertainty [20]. Conejo et al., presented a technical solution for the problem of power generators with large consumers. To minimize the purchase costs and limit the risk of cost fluctuations due to price instability, they used a quadratic mixed-integer mathematical model [14]. Garcia et al., used the mean-variance model and the CVaR model for power generators. The results indicated that the CVaR model has a more conservative approach than the variance-mean model and provides a more stable allocation for risky markets such as spot markets [31]. Glensk et al., used the fuzzy set theory in the optimization process of the electricity sales portfolio.

In this study, a mathematical framework was proposed to identify a set of efficient portfolios, which means maximizing the return of expected return for the predicted risk or minimizing the risk of return for expected return [28]. Liu et al., considered the energy allocation between instantaneous price markets and bilateral contracts as optimizing the energy portfolio with a risk-free asset and a risky asset. They used a quadratic programming model and electricity market historical data for optimizing the studied portfolio [8]. Rebennack et al., conducted a study on optimizing the electrical energy purchasing portfolio in the German electricity market. Their study could determine how much of the energy demand should be generated in the consumer's power plant, how much should be purchased from the instantaneous price market, and how much from contracts. This problem was formulated as a mixed-integer linear programming model without considering the uncertainty conditions and risk measurement in the Gams software [15]. Cohen et al., proposed a multistage variance optimization model for management. To reduce the complexity, they used linear decision rules including the limiting of decision rules set to random parameters [34]. Algariv et al., proposed a retailer portfolio optimization model for future markets, other electricity markets, or a combination of markets. In their study, a multi-factor system was presented to simulate the energy markets with an emphasis on the interaction between retailers and end customers. In their optimization model, the modern portfolio theory was used to identify risk [32]. De Filippo et al., presented a nonlinear optimization approach to electricity market dynamics, which could be used for obtaining tariff proposals. Their approach was based on a stochastic model for residential electricity consumption and a definitive model for large electricity consumers. This model was tested for the Italian energy market data and an extensive analysis of various scenarios was performed [33]. Barati et al., conducted a study to maximize profits and minimize the operating costs of the distribution system by considering the retailer's perspective and the regulation of contracts between suppliers and consumers. In their study, a bi-level optimization model was proposed. This model can minimize the cost of the distribution system with distributed generation and maximize the profits of retailers [5]. Kehunen et al., argued that the conventional risk management optimization methods are typically ineffective when an electricity retailer faces volume and price risk in purchasing from the wholesale market. Thus, they developed a multi-stage stochastic optimization method for managing the electricity contract portfolio. The model considers price uncertainty and electrical loads and uses CVaR to control risk during the planning horizon. The experimental results based on real data indicated that modeling price-load relationships are of particular significance. In a conclusion, a retailer is more sensitive to price uncertainty in terms of expected cost without considering risk. In addition, a risk-averse retailer is sensitive to the incentives of expected risk [19].

Golmuhammadi et al., discussed the green generation portfolio optimization from the retailer's perspective in the market competitive environment. They formulated the uncertainty in electricity price, wind and solar energy generation using stochastic variables. In addition, they used pre-sales contracts to supply a load of customers to reduce the risk caused by purchasing electricity from customers' perspectives. They claimed that consumers can enable retailers to manage the risk and profit caused by attending to the retailer market. In their study, stochastic planning and time series of ARIM, as well as the Monte Carlo method, were used to optimize the clean energy generation portfolio and formulate the problem uncertainties. They considered a set of risk-free bilateral contracts in futures markets, as well as two with instantaneous price markets in Iran including energy pool and energy exchange, from which the customer should purchase by considering risk management [2].

If the price seasonality is considered, triggering an adaptive seasonal behavior which supports the decision of the decision-maker towards its goals, results in illustrating the advantage of reducing the costs and risk. This work proposes a mixed-integer linear formulation for the energy portfolio optimization problem for a large consumer from a buyer perspective. A multi-objective approach is explored to deploy several options to the decision-maker based on its risk pattern. A weighted sum formulation is presented for the expected cost and risk minimization. The binary variables define the procurement decisions and the continuous variables define the electricity procured, the cost of each electricity supplier option, as well as the value of the CVaR [13]. Kokkinos et al., examined the impacts of bio waste-based energy transition through a semi-quantitative evaluation by engaging the relevant social stakeholders' evaluation in the strategic plan. The proposed decision-making tool uses analytics and optimization algorithms to guide competent authorities and decision-makers to sustainable energy transitioning towards decarbonization [17]. Thombs discussed the potential energy future perspectives and proposed a topology. As a result, the authors conclude, that not only the potential energy futures are a simple function of the technologies employed and their scale, but also will be shaped by the social relations that configure societies in general [22]. Falcone, P.M et al., provided the most elective instrument mix for the energy transition in the biofuel industry based on the case of the Italian liquid biofuel sector. The simulation results showed the persistence of negative context conditions would be detrimental for the convergence of expectations, providing clear priorities in setting the energy policy agenda [24]. Falcone, P.M et al, discussed energy and bio-products production based on resource circularity in the tourism industry. Research has shed light on external pressures and internal dynamics to provide a clear direction for policy strategies to support the transition towards a tourism-based circular economy. An integrated SWOT-MLP framework has been built to provide crucial theoretical perceptions for the transition under investigation [21].

The advantage of this study over similar and previous works is that the present study considered two markets with instantaneous prices in Iran's electricity market, including energy pool and energy exchange, in addition to the current contracts. At the same time, the buyer must manage the amount of risk. In other words, the previous executive and economic research is not in the Iranian electricity market and does not give a real answer, since both markets have a significant impact on costs with spot prices and current contracts in Iran. Therefore, the model is designed to match the structure of the Iranian electricity market and efficiency.

Accordingly, the present study aimed to study the goals which should be considered for designing an electricity portfolio and selection of the optimal level for applied planning.

3- RESEARCH METHODOLOGY

The present study was applied in terms of purpose. The research design was field experimental while the data collection method was the library and using articles from scientific databases. Data collection tools included databases, articles, scientific books, and databases from the studied organization. In addition, MATLAB software was used for data analysis. Due to the small number of industrial subscribers, the whole population was studied. To use the model and numerical studies in the Iranian electricity market, real information was used from the historical prices in 2018.

3-1- Decision-making Framework

They use bilateral contracts to supply part of their energy. A bilateral contract is a treaty between two parties outside the electricity market environment. In this study, it is assumed that the consumer has the following eight contracts:

- Contract C1 is to cover the whole summer (whole period), which is prepared and signed one year before consumption
- Contract C2 is to cover the whole summer (whole period), which is prepared and signed one year before consumption
- Contract C3 is to cover the first half of June, which is prepared and signed in the first half of July
- Contract C4 is to cover the second half of June, which is prepared and signed in the second half of July
- Contract C5 is to cover the first half of July, which is prepared and signed in the first half of July
- Contract C6 is to cover the second half of July, which is prepared and signed in the second half of July
- Contract C7 is to cover the first half of August, which is prepared and signed in the first half of August
- Contract C8 is to cover the second half of August, which is prepared and signed in the second half of August

Consumers attend the electricity market to purchase at an instantaneous price. Transactions in the energy pool and energy exchange are instantaneous and depend on the market price. Due to the uncertainty in the price of these two markets, these decisions are always associated with their complexities. Prices are expressed in different scenarios. Each scenario is related to the realization of the price of pool and energy exchange in all periods (i.e. each scenario represents a scenario of energy purchase with its probability). In using stochastic planning, the problem of purchasing the optimal electrical energy portfolio is a multi-stage problem that can be solved in form of a stochastic planning model. In the present study, a period of three months, including six times subscales was considered so that each subscale represented half of each month in summer. Therefore, the planning

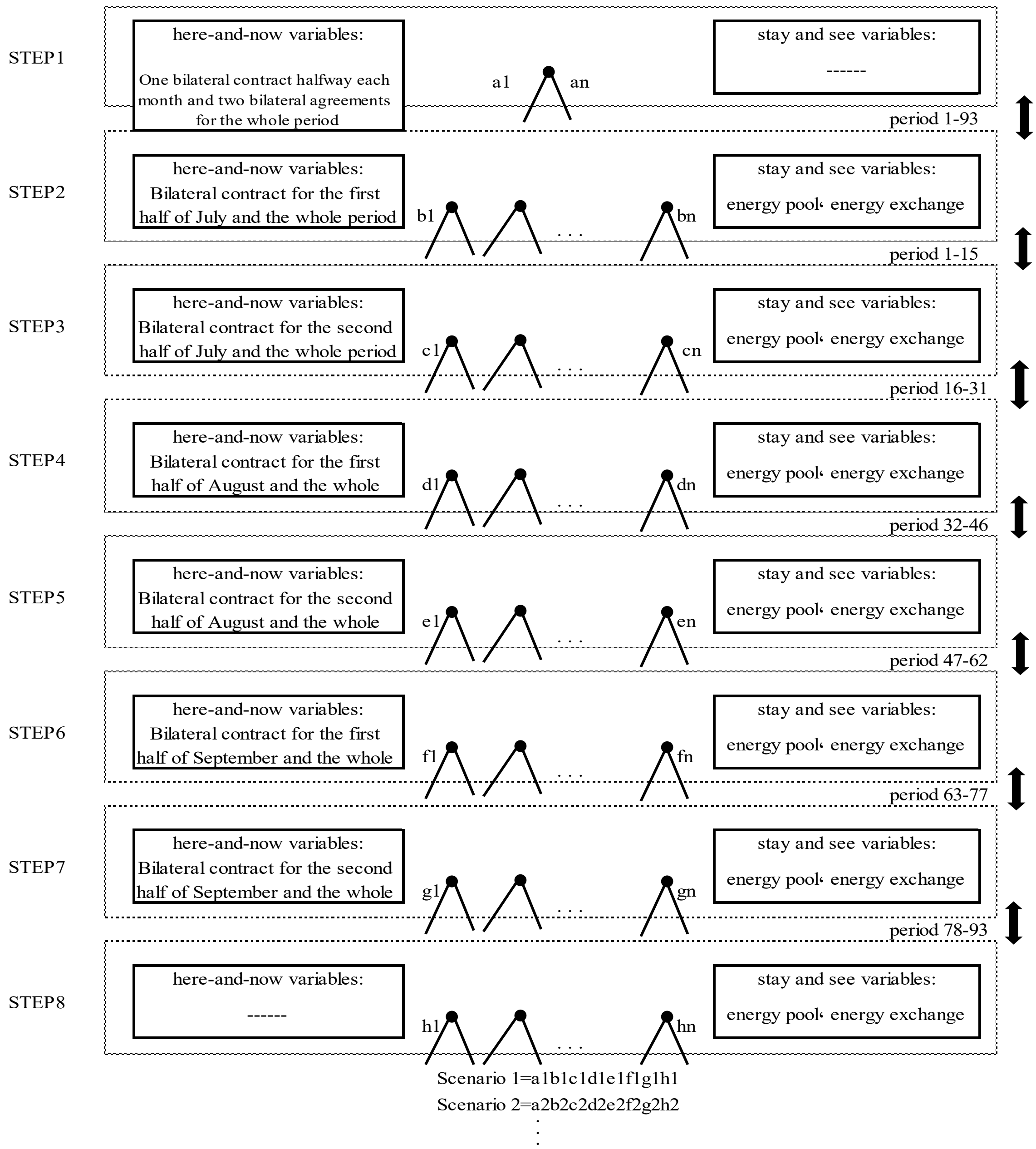


Fig. 1: Decision-making framework from the consumer's perspective

horizon was 93 days of summer. The main decision-making variables in this issue include determining the amount of energy purchase from bilateral contracts, electricity purchase from the instantaneous price market, energy pool, and energy exchange. At all periods, the amount of purchase from bilateral contracts related to the whole period or each half of the month was concluded without knowing the future market prices, and was not related to the realization of scenarios. Thus, these types of decision-making variables are called here-and-now variables. Instead, the variables related to the energy pool market and energy exchange are close enough to the time of consumption and are called stay-and-see variables [30]. Fig. 1 shows the decision-making framework from the consumer's perspective. As shown, the number of steps and the type of decision variables in each step is specified. In addition, several paths are specified in each node. The combination of these nodes leads to the production of a possible scenario. Each scenario is the realization of a complete path from the root node to the last node.

3-2- Modeling

In this section, stochastic planning for the problem of purchasing the optimal portfolio of electrical energy is presented, considering the explanations provided in the pre-model mathematical section.

3-2-1- Purchasing Energy from Energy Pool and Energy Exchange

The cost of purchasing in energy pool and energy exchange is as follows (1).

$$C_{tw}^{C} = \sum_{t=1}^{T} \left(\lambda_{tw}^{P} P_{tw+}^{P} \lambda_{tw}^{M} P_{tw}^{M} \right) \quad (1)$$

Where λ_{tw}^{p} presents the price of electrical energy in the energy pool and λ_{tw}^{M} represents the price of electrical energy in energy exchange. In addition, p_{tw}^{p} and p_{tw}^{pM} indicate the energy purchased from the energy pool, and the energy exchange in scenario w and time t. Furthermore, C_{tw}^{S} presents the final cost of purchasing from instantaneous markets.

3-2-2- Purchasing From Bilateral Contracts

Consumers can use bilateral contracts to supply parts of their energy [6]. A bilateral contract refers to a contract between two parties outside the electricity market, and it is assumed that the price of contract λ_{C}^{C} is independent of the market price. The cost of purchasing from the bilateral contract in scenario w and the whole period of contract C is introduced with C_{CW}^{C} and obtained as follows (2):

$$C_{CW}^{C} = \sum_{c=1}^{nc} \sum_{t=1}^{T} \lambda_{ctw}^{C} p_{cw}^{C} d_{t} \quad (2)$$

Where λ_{ctw}^{C} represents the price of purchasing from contract c at the period t, and $p_{cw}^{C} d_{t}$ indicates the power purchased from the contract at the period t, while NC refers to the number of bilateral contracts. Eq. 3, which is considered as a constraint, allows energy to be purchased from a given contract during a time, and if contract c is selected in scenario w, S_{cw} is a binary variable which equals to 1; otherwise, it is zero.

$$0 \le \sum p_{cw}^{C} d_{t} \le p_{c}^{C,max} S_{cw} \quad (3)$$

In this study, a capacity was provided for contracts. In addition, the generated power $p_{cw}^{C} d_{t}$ is enclosed by its own upper and lower limits, as given in Eq. 4:

$$p_{c}^{C,min} \le p_{cw}^{C} d_{t} \le p_{c}^{C,max} \quad (4)$$

$$\bigcup_{i=1,\ldots,n_{c}} T_{c,i} = T_{c} \quad (5)$$

In Eq.5, the planning horizon of each contract is usually divided into several subsets of periods based on the prices of the energy pool and energy exchange.

3-2-3- Model of Conditional Value at Risk

Markowitz was the first person who has stated the use of the relationship between risk and return in form of portfolio theory, and the risk became a quantitative criterion for the first time through the proposed model [3]. In modern portfolio theory, the risk is defined as the variability of total returns around the average, and is calculated using the variance criterion. Assuming the distribution is normal, variance is an acceptable measure of return on risk. However, real-world research and theoretical debates reject this assumption. Thus, it is not a good criterion of risk when the distribution of returns is asymmetric, and because the variance fines favorable price moves upwards as much as undesirable price moves downwards [25]- [26]. A logical investor with a short-term vision not only welcomes positive stock price fluctuations, but also seeks a way for measuring the negative fluctuations of the portfolio and selects the optimal portfolio with the least adverse risk on average based on the results. Such approach is the main tool for risk measurement and management [27]-[18]. Value at Risk (VaR) refers to the maximum loss that we expect the portfolio to have in each time horizon at a certain level of confidence. Summarizing risks into a single number is considered one of the significant advantages of this tool. Unlike the simple concept of VaR, its calculation is associated with difficulties [23]- [16].

VaR is the maximum amount of damage at the confidence level(1-α) during a specified period. In this model, risk occurs when the daily loss is higher than VaR. In a fully designed model, the probability that the realized loss deviates from the specified VaR will be ξ %. In the VaR measurement model, the confidence of the investor at his investment portfolio at level α is determined to not lose more than Y Rls during a T period in the future. The variable Y, VaR, is related to the specified portfolio, being obtained from Eq. 6:

$$Y = -CDF^{-1}\ (1\text{-}\alpha) \quad (6)$$

Where $-CDF^{-1}$ represents the inverse cumulative distribution function for investment profit V and α indicates the confidence level for the investor. Calculating VaR statistically means finding the critical value for the desired probability level [3]. Since the probability distribution of returns over time is not constant, there are problems in calculating VaR. The inconsistency of this criterion is one of the main problems with VaR. CVaR has been introduced for the evolution of VaR in recent years. This criterion estimates the expected loss at or above VaR at a certain confidence level. Thus, this view is more conservative than the previous one. Due to the precautionary aspect of CVaR and its higher application during recent years, the present study focused on this criterion as a risk indicator. The measurement model of CVaR has a coherent criterion unlike the VaR model, and is a coherent criterion with four characteristics of uniformity, addibility, positive homogeneity, and uniform transmission. While addibility is one of the mental principles of every investor, the VaR model is not considered coherent due to its lack of this feature. For instance, the addibility rule is extremely critical in discussing the capital adequacy requirements of banks from a regulatory perspective. Consider the branches of a bank. If the capital

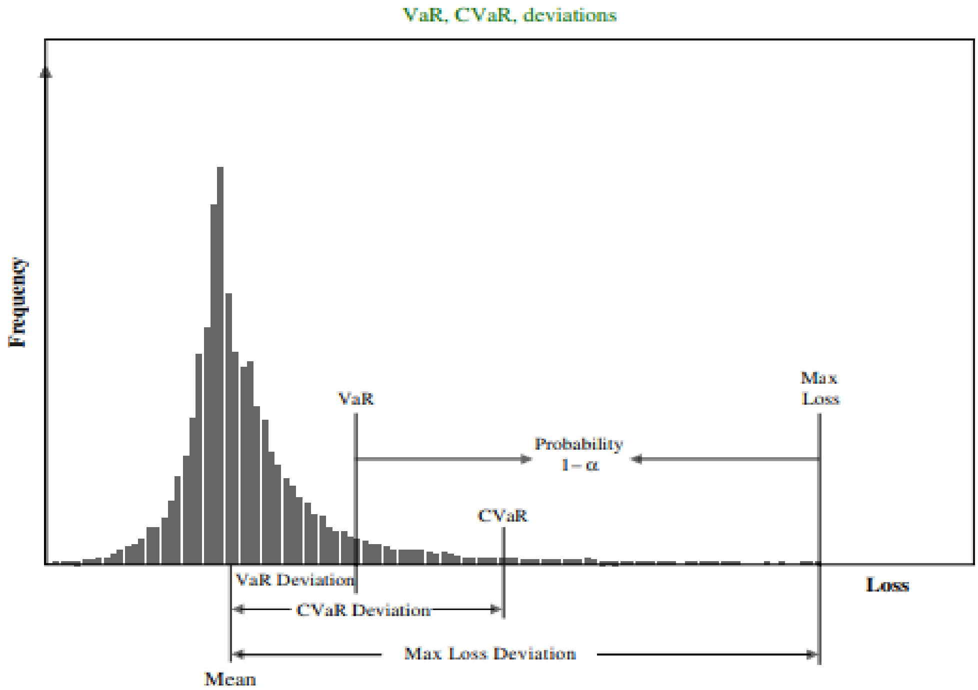


Fig. 2. Position of value at risk and conditional value at risk [3]

requirements of each branch are specified based on its risk, the supervisor can be sure that the total capital of the branch will be sufficient based on the addibility rule. Based on the VaR criterion, the set risk will be equal to the total risk of all branches. This criterion was developed in a study [3] to cover coherence indicators.

Finally, the VaR method has an undesirable property due to the lack of a subset, making it difficult to calculate when using the scenarios, because it is a non-convex and uneven function and has several local extreme values. CVaR, which has convex, subset, and even properties and calculates losses greater than VaR is the appropriate criterion. Fig. 2 shows the position of VaR and CVaR [3]. Eq. 7 indicates that the CVaR value measures the expected loss if it increases more than VaR.

$$CVaR = E(Loss \setminus Loss > VaR) \tag{7}$$

In addition, the y-vector represents the uncertainties affecting the loss. Therefore, the return on portfolio x is the sum of the returns on each capital in the portfolio on a ratio of xj. Since loss is a negative return on expected return, it is defined as Eq. 8:

$$f(x,y) = -\left[x_s y_s + x_c y_c\right] = -x^T y \tag{8}$$

Where x_s represents the portfolio ratio, used in the spot market, risky assets, and x_c is used in risk-free assets. The performance function based on CVaR is described as (9) and (10) (Rockafer and Uriasov, 2010) [21-35].

$$CVaR = F_a(x,\xi) = \xi + (1+a)^{-1} \int_{y\grave{o}R} w\left[f(x,y)-\xi\right]^{+} p(y)\,dy \tag{9}$$

$$\psi(x,\xi) = \int_{f(x,y)\le\xi} p(y)\,dy \tag{10}$$

Where p(y) is a function of density y, which is a function of the cumulative distribution $\psi(x,\xi)$ for the loss associated with x. In addition, it is assumed that VaR for a particular portfolio is underconfidence at level α. In the above Eq. F_a is an approximation obtained through the Monte Carlo simulation. When applying Monte Carlo simulations, $F_a(x,\xi)$ is obtained as a distribution F_a by sampling the probability distribution in y:

$$F_a(x,\xi) = \xi + \frac{1}{w(1-a)} \sum_{w=1}^{w} \begin{bmatrix} f(x,y) \\ -\xi \end{bmatrix}^{+} \tag{11}$$

Where ω represents the sample number p (y). The estimated function $F_a(x,\xi)$ is convex and linear ξ is a piece being minimized by linear search techniques or a rudimentary programming problem. The risk of uncertainties should be considered in the decision-making process for energy supply. In this study, the CVaR criterion was used to model the risk of cost changes, and CVaR is in fact the mathematical expectation $(1-a)*100\%$ of the scenarios with the largest cost. CVaR is expressed by the mathematical model (12) [19-35]:

$$Cvar = min\xi + \frac{1}{w(1-a)}\sum_{w=1}^{w}\pi_w\eta_w \quad (12)$$

To eliminate the non-negative constraints of the above function, an auxiliary variable $\eta_w\,(w=1,\ldots,w)$ was added to the model with other constraints. Equations 13-15 indicate this issue.

$$\begin{aligned}&\sum\nolimits_{t\in T}(\sum\nolimits_{c\in cDt}\lambda^c_{ctw}P^c_{cw}d_t + \lambda^p_{tw}p^p_{tw}\\ &+\lambda^M_{tw}P^M_{tw}) - \xi \le \eta_w\end{aligned} \quad (13)$$

$$-\xi - \eta \le 0 \qquad \forall_w \in w \quad (14)$$

$$\eta_w \ge 0 \qquad \forall_w \in w \quad (15)$$

3-2-4- Unpredictable Constraint

Every scenario including one answer may be the same during the planning period, when the scenarios are the same. Afterwards, the values of the decision variables are equal at this step. In other words, this constraint is considered as a source to limit the decision variables associated with a node with the same values in different scenarios.

$$\begin{aligned}&Sc_w = Sc_{w+1} \quad , \quad \forall_c, w\in Z\\ &If\ Sim(w,k)=1\end{aligned} \quad (16)$$

$$P^c_{cw} = P^c_{c_{w+1}} \quad , \quad \forall_c, w\in Z \quad (17)$$

$$M(w,k) = \begin{cases}1 & step \quad K\\ 0\end{cases}$$

$$if\ the w+1 and\ w scenarios\ are\ simultaneous$$

3-2-5- General Model of Multi-objective Optimization

The multi-objective optimization model for the problem of the present study is expressed as equations 18- 29:

$$\begin{aligned}&min\sum\nolimits_{w\grave{o}W}\pi_w\sum_{t\grave{o}T}(\sum_{c\grave{o}CD_t}\lambda^c_{c\,tw}P^c_{cw}d_t + \lambda^p_{tw}P^p_{tw}\\ &+\lambda^M_{tw}P^M_{tw}) + \beta\left(\xi + \frac{1}{1-a}\sum_{w\grave{o}W}\pi_w\eta_w\right)\\ &st.\end{aligned} \quad (18)$$

$$P^M_{tw} + P^P_{tw} + \sum_{c\grave{o}CD_t}P^c_{cw}d_t = \quad (19)$$

$$P^M_{tw} \qquad \forall t, \forall w$$

$$P^D_{tw} \ge P^D_0\ \forall t, \forall w, \forall w\in W \quad (20)$$

$$0 \le P^c_{cw}d_t \le P^{c,max}_c \quad ; \quad \forall c\in C \quad , \quad \forall t\in CD_t \quad (21)$$

$$P^c_{ctw} = 0, \forall_c \in C,\ \forall_t \in T\setminus CD_t,\ \forall_w \in W \quad (22)$$

$$P^{c,min}_c Scw \le \sum_{c\,\in\,CD_t}P^c_{cw}d_t \le P^{c,max}_c Sc_w \quad \forall_c, \forall_w \quad (23)$$

$$Sc_w = Sc_{w+1} \qquad \forall c, w\in Z \qquad If\ sm(w,k)=1 \quad (24)$$

$$P^c_{cw} = P^c_{c_{w+1}} \qquad \forall c, w\in Z \qquad If\ sm(w,k)=1 \quad (25)$$

$$\begin{aligned}&\sum_{t\in T}(\sum_{c\grave{o}CD_t}\lambda^c_{c\,tw}P^c_{cw}d_t + \lambda^p_{tw}P^p_{tw}\\ &+\lambda^M_{tw}P^M_{tw}) - \xi \le \eta_w, ^{(27)}\forall_w\\ &\eta_w \ge 0 \quad \forall_w \in W\end{aligned} \quad (26)$$

$$P^p_{tw}, P^m_{tw}, \xi, \eta_w \ge 0 \quad \forall_c, \forall_t, \forall_w \quad (28)$$

$$S_{cw} \in \{0,1\}\, \forall_c, \forall_w \quad (29)$$

Equation 18 represents a function of the overall objective and involves costs and risks. In this regard, costs are minimized by selecting among possible scenarios. In addition, purchasing from the instantaneous price markets and buying from bilateral contracts, as well as the amount of CVaR were included in the confidence level. The discrete cost distribution $(a-CVaR)$ is the expected cost of scenarios with higher costs, which β is a risk factor describing the way of thinking about the level of risk and is a number that strikes a balance between the mathematical expectation of cost and risk. In other words, it is a weighting factor that balances the expected costs of purchase and risk, and depends on consumer preferences. In addition, $\beta\grave{o}[0,10]$. A risk-averse consumer prefers to meet demand and reduce risk. Thus, he selects a larger amount of β risk factors to measure the risk. In addition, another consumer can take risks in reducing purchase costs. Thus, the selected value of the weighting factor tends to zero. Constraint 19 ensures that the required energy is provided in all periods and scenarios. Based on

```
Generate random population.
Calculate the fitness of each chromosome.
X*=the best solution.
While (t < maximum number of iterations)
Select a pair of chromosomes as parents.
Perform crossover and mutation to generate new chromosomes.
Merge all the chromosomes and select the new population.
Update the X* if there is a better solution.
t=t+1
End while
Return X*
```

Fig. 3. Pseudocode of the genetic algorithm.

constraint 20, the required demand should be equal or greater than five MW per hour. Constraint 21 determines the range of energy consumed by each contract in each period. Based on constraint 22, it is impossible to purchase energy outside the planning horizon of any contract. Constraint 23 determines the upper and lower limits for the energy consumption resulting from the contracts in each subset of periods. Constraints 24 and 25, model the unpredictable constraints. Equations 26 and 27 provide the constraints associated with calculating the conditional value at risk. Eq. 28 represents the nature of the decision variables in the model and Equation 29 represents the binary variable and determines whether contract c is selected in step w. If this happens, the variable will select a value of one; otherwise, it will select a value of zero.

In this article, a multi-objective mathematical model is proposed for the electricity market portfolio, required by the industrial Consumptions problem under uncertainty conditions. According to the article references such as [36]- [37]- [38], to solve the real-world problems the Genetic algorithm, the known meta-heuristic algorithms were applied.

3-3- Genetic Algorithm (GA)

Genetic algorithm is a common optimization tool for engineering problems, which was introduced by John Holland from the University of Michigan in 1975 [35]. Genetic algorithms are special types of evolutionary algorithms that utilize biological anabolic techniques such as inheritance and mutation. The genetic algorithms use the principles of Darwin's natural selection to find the optimum formula for estimation or matching patterns. Genetic algorithms are programming techniques that make use of genetic evolution as a problem-solving scheme. The problem to be solved is the input and the solutions are coded per scheme, which is called the fitness function that evaluates every candidate. Two search operators are present in this algorithm: Crossover and Mutation. Mutation creates a neighborhood based on the offspring, while crossover selects two solutions as the parents and creates two offspring solutions by combining them, and thus, searching for the possibility space of the solution [35]. The algorithm performs the focus and variety phases of metaheuristics blindly in the solution space. The pseudocode of the genetic algorithm in which the mentioned steps are implemented, is in Figure 3.

In this case, the following chromosome is used to allocate energy to each source in Figure 4.

3-3-1- Operators

A genetic operator is an operator used in genetic algorithms to guide the algorithm towards a solution to a given problem. There are three main types of operators (mutation, crossover, and selection), which must work in conjunction together for the algorithm to be successful [35].

3-3-2- Adjust the Parameters of the Genetic Algorithm

Taguchi method is applied to select the best value of each required parameter in metaheuristic algorithms. This method was developed by Taguchi to select the best value of each parameter, instead of taking all possible experiments [35]. First, we set the parameters of the genetic algorithm, using the Taguchi method. The parameters of the genetic algorithm are as shown in Table 1.n

Using the Taguchi method and its implementation in Minitab software, orthogonal L9 is suggested as shown in Table 2.

The best values of each parameter of the problem are obtained according to the SN diagram for the GA (Figure 5). The best value of each parameter in each problem is the parameter level with the highest SN value. For example, 0.7, 0.4,50,50 are the best values for Pc, Pm, MaxIt, and nPop on the first test problem.

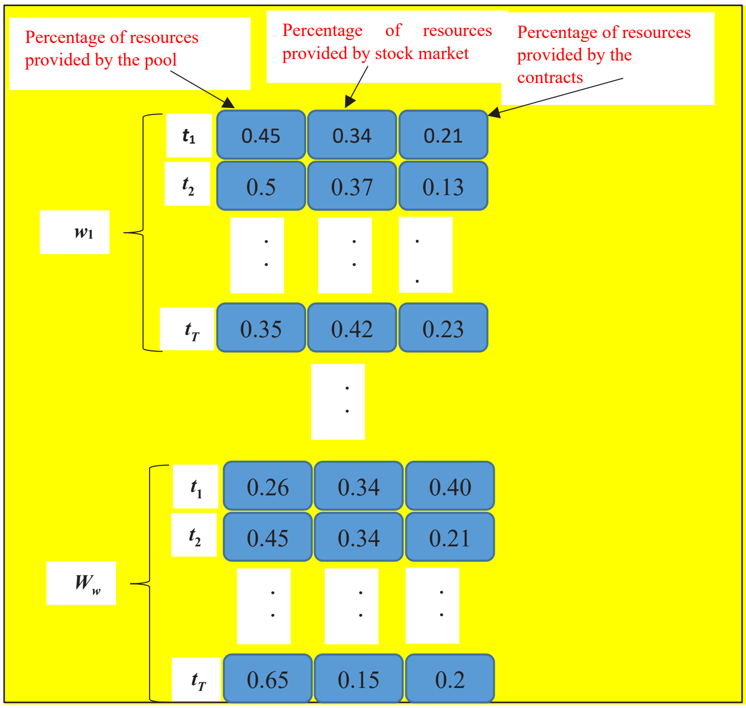


Fig. 4. Images related to problem chromosomes

Table 1. Values of genetic algorithm parameters for different levels

Parameters	Parameters levels		
	1	2	3
nPop	50	80	100
MaxIt	50	100	150
Pc	0.6	0.7	0.8
Pm	0.2	0.4	0.5

Table 2. The main solution for each Taguchi experiment for *GA*.

Experiment #	nPop	MaxIt	Pc	Pm	Response
1	50	50	0.6	0.2	52748161.1896
2	50	100	0.7	0.4	52808076.1397
3	50	150	0.8	0.5	52864051.3403
4	80	50	0.7	0.5	52873317.2994
5	80	100	0.8	0.2	53161277.9414
6	80	150	0.6	0.4	52752701.2071
7	100	50	0.8	0.4	52785116.6811
8	100	100	0.6	0.5	53143999.6440
9	100	150	0.7	0.2	52934637.1796

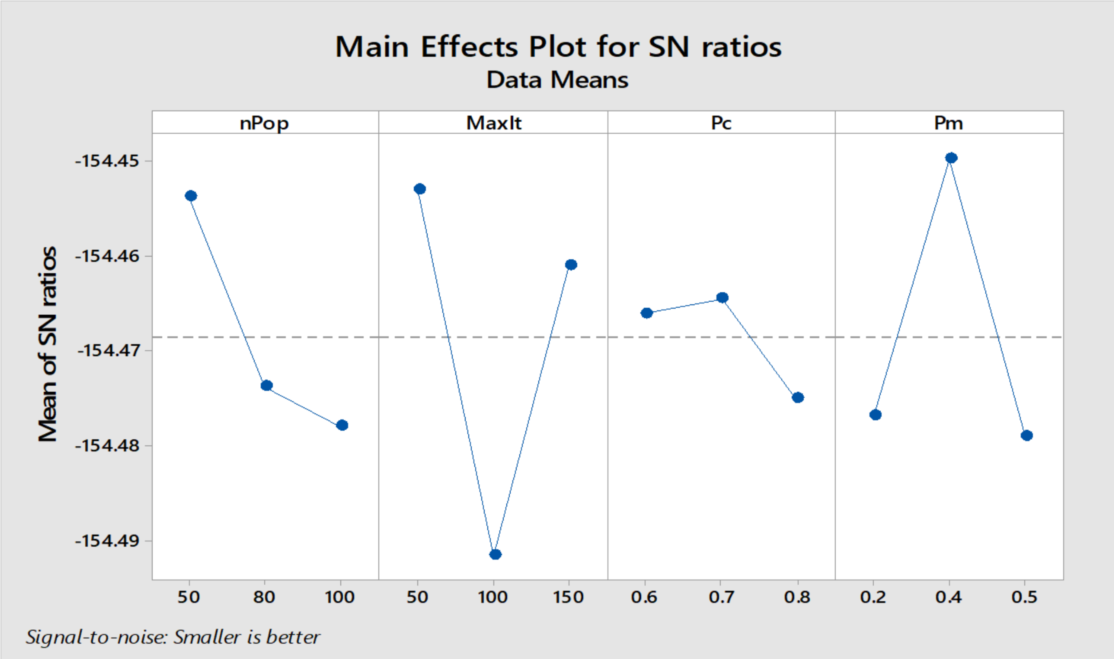


Fig. 5. The SN diagram for the NBL-GA

4- RESULTS

3- 1- Implementing the model in the Iranian electricity market

To use this model and numerical studies in the Iranian electricity market, some real information was used from the historical prices in 2019. Instantaneous prices are found using the sets of $\{\lambda_1^P,\ldots,\lambda_{Nt}^P\}$ and $\{\lambda_1^M,\ldots,\lambda_{Nt}^M\}$ from energy prices in periods $t=1,\ldots,N_t$ and λ_t^M through a completely stochastic process based on the empirical probability distribution used in scenario analysis. Each scenario shows the occurrence of a specific group or a combination of prices for all planning horizons. Thus, $\{\lambda_1^P \dots, \lambda_{Ntw}^P\}, \forall_w \in$ represents a set of stochastic variables $\{\lambda_1^P,\ldots,\lambda_{Nt}^P\}$ and $\{\lambda_1^M,\ldots,\lambda_{Nt}^M\}$, where w indicates the scenario of scenarios, Ω shows the set of scenarios and represents the number of courses on the planning horizon. Each scenario has a probability of occurrence π_w, so that the sum of the probabilities of all scenarios equals one. Using the current data, 64 scenarios with a similar probability of occurrence were created for a summer planning horizon in the form of six subsets including half of each summer month. Instantaneous market prices are shown using a decision tree, in which each node is the start of two branches, and each branch equals the probable price for the analyzed period. Different price scenarios for all periods are achieved through the branch from origin. The number of scenarios that should be considered is a function of the number of periods for the energy supply planning horizon. In this model, eight bilateral contracts were considered so that two contracts were used for the whole period and one contract for each half of the month. The data relating to each period with the energy constraints and reference prices for each contract are shown in Table 1. The instantaneous prices of the market were displayed using a decision tree. For this purpose, two branches were taken from each node and each node equals the probable price for the analyzed period. Different price scenarios for all the periods were achieved through the branches of origin. The number of scenarios was a function of the number of planning horizons of the energy supply problem. In this model, the value of the parameter was considered 0.95, for which various values can be considered in the sensitivity analysis.

Fig. 6 displays the different amounts of energy purchase cost from energy pool and energy exchange related to summer 2019. Fig. 7 illustrates the different amounts of energy purchase costs from contracts during different time horizons. The data shown in Table 3 and Fig. 7 were used for conducting simulations and numerical calculations. In addition, MATLAB software and genetic algorithm were used for implementing the model and sensitivity analysis. The specifications of the components of the energy purchase portfolio were given in the previous section. It is assumed that this portfolio is only part of the electrical energy required by the large consumer. After implementing the model in MATLAB software, the collected data were applied in the model and the sensitivity value of β was analyzed in the interval $[0,10]$. Table 4 shows the expected cost values (cost expectation), CVaR (risk expectation), an objective function for different β values.

As shown in Table 4, increasing the β value increases the risk aversion of decision-makers and energy supply costs while the amount of risk (risk expectation) decreases. In addition, a positive relationship was observed between increasing the β value and risk aversion. Fig. 8 shows the efficient frontier curve based on the expected energy costs versus CVaR risk levels for different β values.

Table 3. Energy supply contracts

C		t	$P_C^{C,max}$	$P_C^{C,min}$	P_C^C
		day	Kwh	Kwh	Rial
whole period	1	1 - 93	1000	200	710
	2	1 - 93	1500	500	750
June	3	1 - 15	1000	200	660
	4	16 - 31	1500	500	700
July	5	32 - 46	1000	200	741
	6	47 - 62	1200	300	780
August	7	63 - 77	1000	200	728
	8	78 - 93	3000	600	640

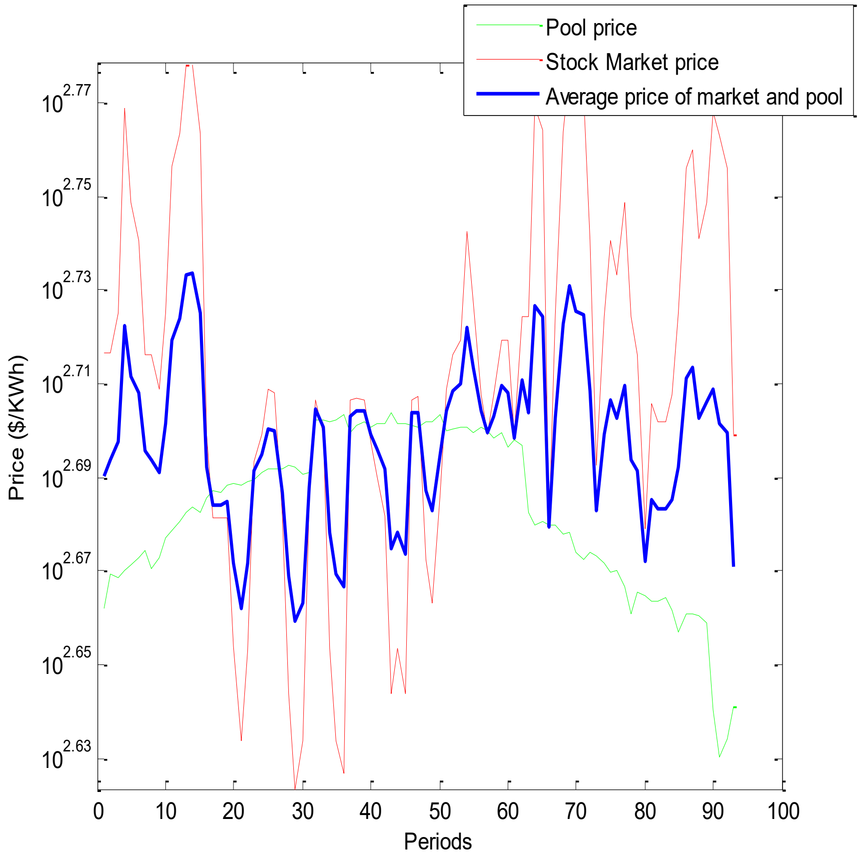


Fig. 6. Different amounts of energy purchase cost from the pool, stock market, and their average in different periods

If the risk is ignored (β value is considered zero), the expected cost of energy purchase is calculated as 8.463 million Rls. If the risk is considered, the expected cost value and the CVaR value face no changes for the values more than β=5. Thus, the expected cost becomes 8.863 million Rls by considering β = 5 that increases by 2.6. Instead, the amount of Cvar reduces by 6.8%.

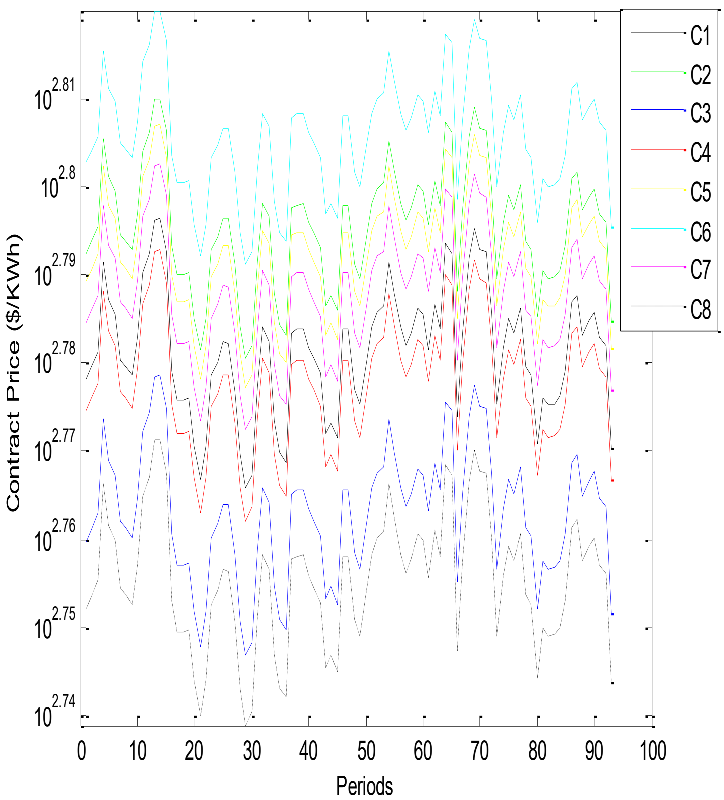


Fig. 7. Different amounts of energy purchase costs from contracts in different periods

Table 4. Expected cost values, CVaR, and objective function for different β values

β	Expected Cost (Million Rls)	CVaR (Million Rls)	The objective function (Million Rls)
0	8.46323024	9.45410458	8.46323024
0.15	8.517935505	9.15732843	9.96653477
0.25	8.638434252	8.86464308	10.844595
0.5	8.675555119	8.81748028	13.0842953
1.25	8.678465237	8.81503754	14.1742563
2.5	8.678465237	8.81503754	14.1742563
5	8.682616477	8.81174255	52.7413292
8	8.682616477	8.81174255	52.7413292
10	8.682616477	8.81174255	52.7413292

Decisions to purchase electrical energy with higher levels of risk aversion and more participation in bilateral contracts are recommended in comparison to spot price markets and purchasing from the energy pool. Purchasing from bilateral contracts reduces the market price fluctuations. Such behavior can be observed in Figs. 9 -11 for different β values. In addition, the share of purchases from spot price markets, especially energy exchange, increases at a low level of risk aversion in purchasing portfolio. Although the purchase of energy through bilateral contracts has higher costs, it becomes a tool for covering effective risk due to its low volatility. As displayed in Fig. 9, when β is 0.15, a new scenario is created, because it is possible to reduce the CVaR by 3.2% and increase the cost by 0.64% in the expected cost. This special scenario is important for the decision-makers who are risk-averse and reluctant to control the risk, but tend to purchase a portfolio with a low level of risk coverage. In addition, it is significant for the decision-makers who are risk-averse and manage risk. The value of CVaR is critical based on the expected cost value. Based on Fig. 11 and Table 4, the value of β = 5 was selected. The relationship between the risk cost and the expected cost is more stable when the

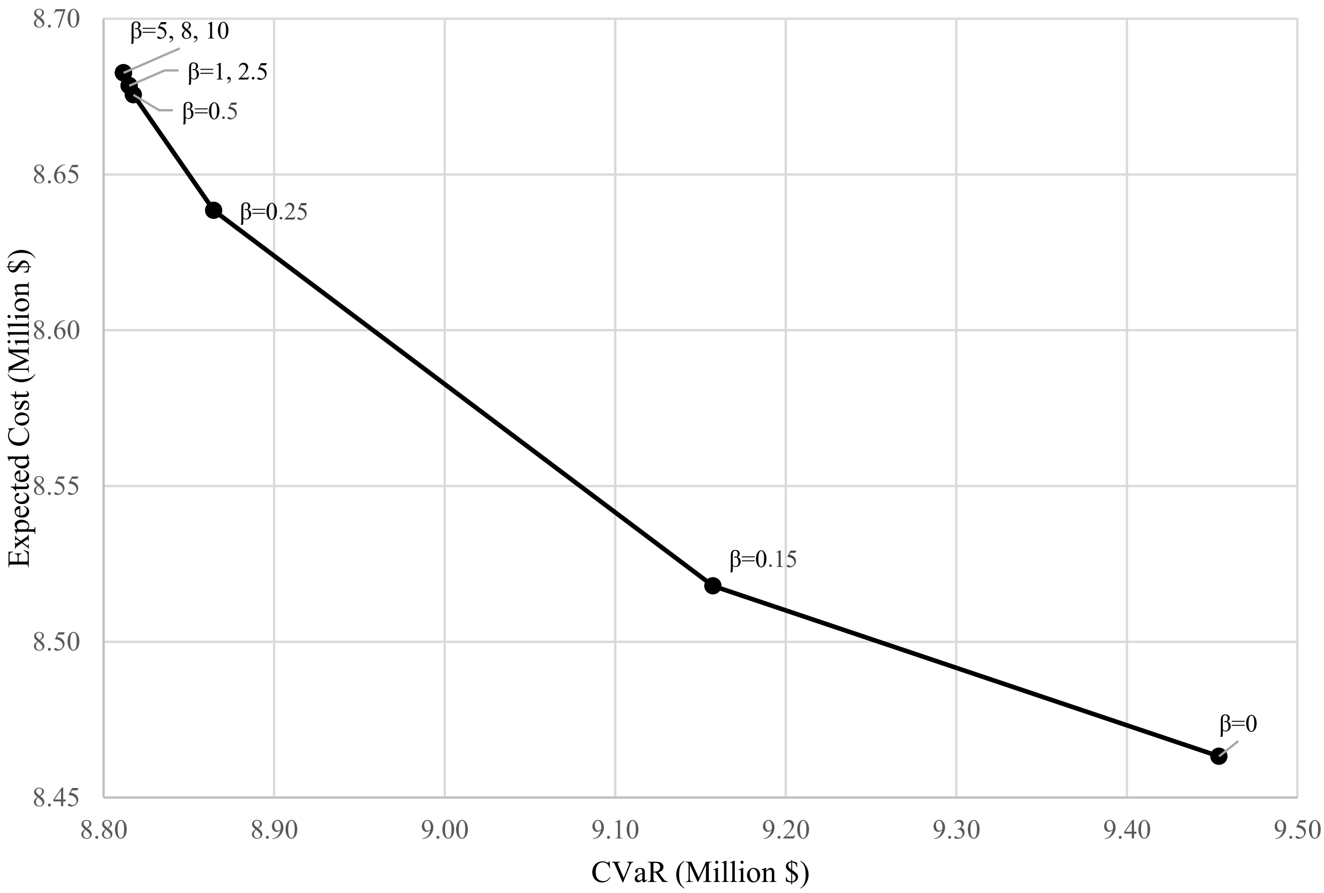
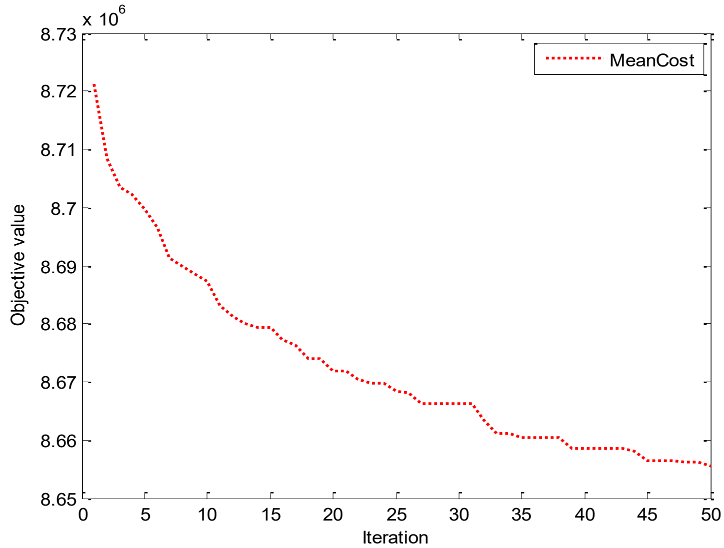


Fig. 8. Expected cost versus CVaR for different β values

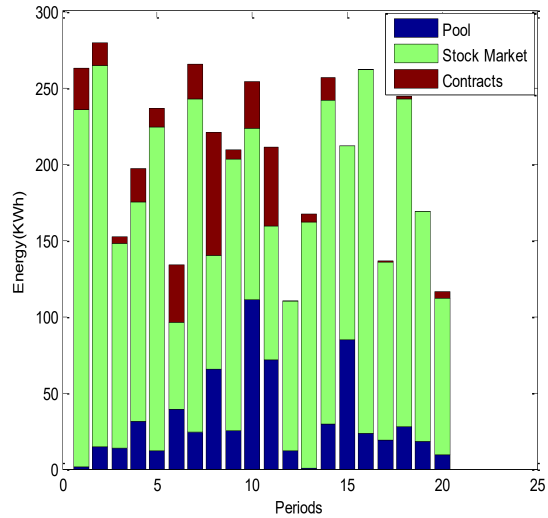
value of β increases. However, the value of the objective function increases by keeping a constant and similar level of relative risk $\beta \geq 5$. Finally, the best answer for the cost of energy supply was proposed at β* = 5, that in β*, the cost from level β = 5 had a 2.5% increase in the expected cost and 6.73% reduction in risk.

5- DISCUSSION AND CONCLUSION

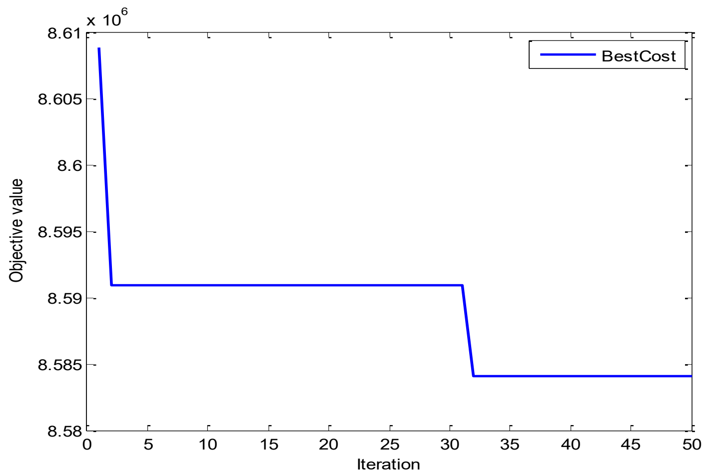
This study presented an efficient approach based on stochastic planning for determining the electrical energy purchasing portfolio of the large consumer. The proposed approach can minimize the purchasing costs by considering a level of risk. The presented model is in the field of planning issues and proposing the portfolio of electric energy. It should be noted that previous studies mostly focused on the sales portfolio of electrical energy and there are few studies on how to purchase the optimal electrical energy portfolio from the consumer's perspective. This study presented a practical model for large consumers in the Iranian electricity industry, including a set of bilateral contracts in risk-free futures markets and the use of two markets with instantaneous prices, including energy pool and energy exchange by considering the planning horizon to provide energy carriers. In addition, uncertainty in the instantaneous prices of the subscribers' electrical energy market was considered in the decision-making, considering that uncertainty expands the space of scenarios and complicates the decision-making process. The proposed model used the concept of CVaR to eliminate unfavorable scenarios in the costs of scenarios. Increasing the importance of risk in the problem reduces the risk, but increases the cost function. Furthermore, each scenario presents a different answer for energy supply. The energy supply framework reflects many situations in the real world. In this study, the real data of Iran were used. Purchasing energy from bilateral contracts is normally more expensive, while it reduces the risk of the transaction. Due to the lack of fluctuations, it is a kind of financial coverage to deal with the fluctuations related to the instantaneous prices of electrical energy. The maximum cost in the cost function is related to the factors with higher levels of risk aversion (higher β parameters). Thus, bilateral electrical energy purchasing contracts are selected before the planning horizon, even when the instantaneous price of markets is less than the reference price of bilateral contracts. Furthermore, the price of the energy pool fluctuates less in the instantaneous prices markets of electrical energy. In conditions β*, purchasing



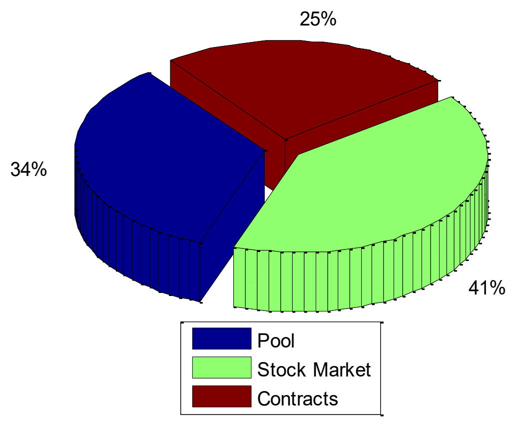
A) The average of the objective function for different repetitions of the algorithm



B) Energy purchased at the first 20 periods for a single scenario

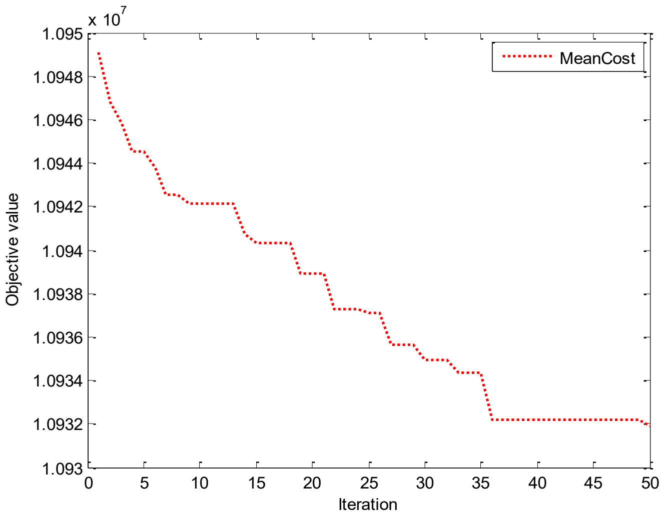


) Objective function values for different repetitions of the algorithm

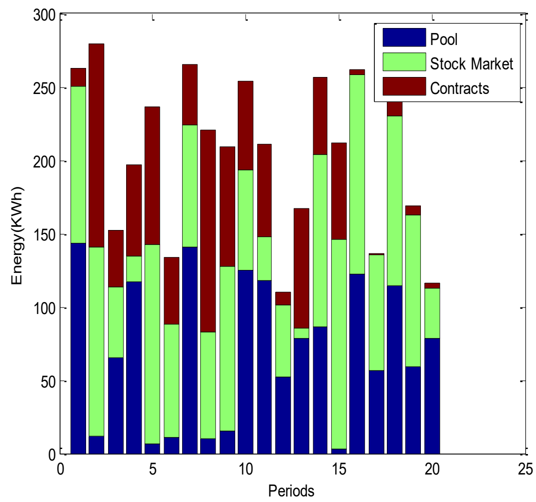


C) Energy purchased in the first period for all scenarios

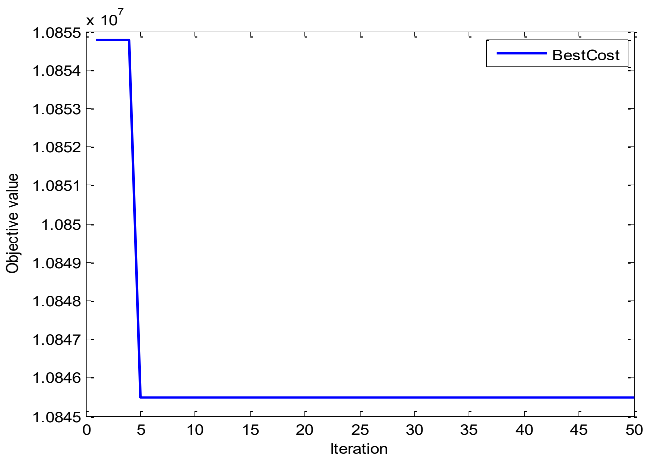
Fig. 9 Obtained results for β=0 values



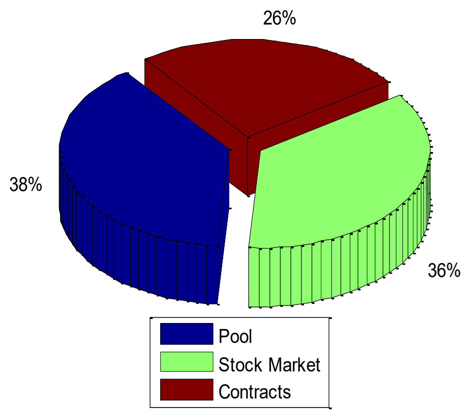
A) The average of the objective function for different repetitions of the algorithm



B) Energy purchased in the first 20 periods for a single scenario

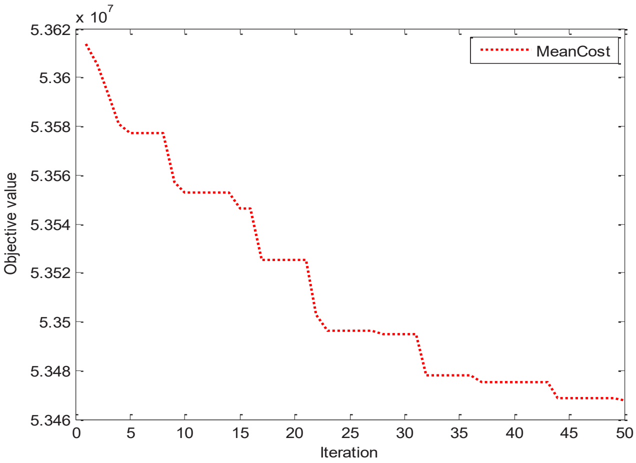


C) Objective function values for different repetitions of the algorithm

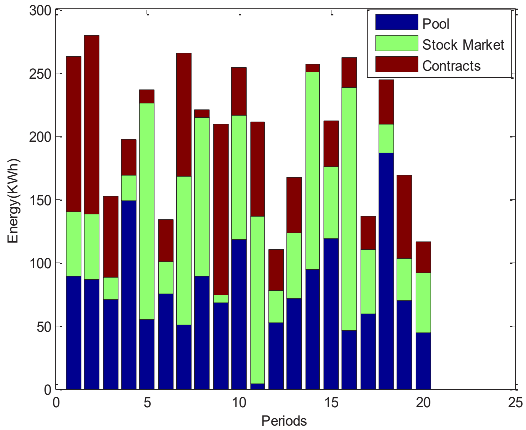


D) Energy purchased in the first period for all scenarios

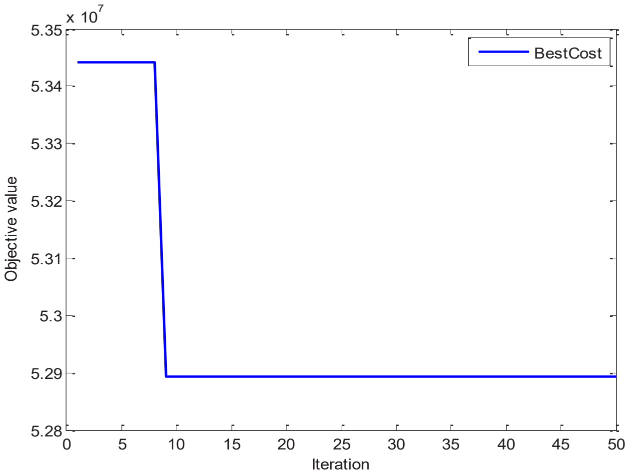
Fig. 10. Obtained results for β=0.25 values



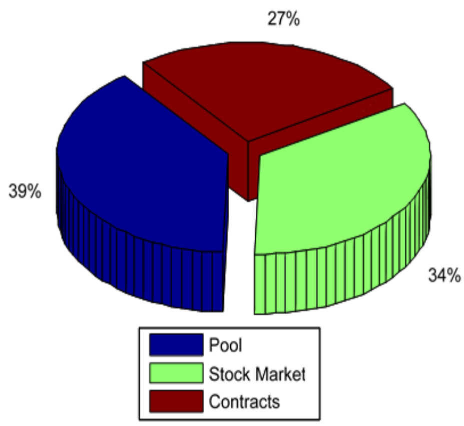
A) The average of the objective function for different repetitions of the algorithm



B) Energy purchased in the first 20 periods for a single scenario



C) Objective function values for different repetitions of the algorithm



D) Energy purchased in the first period for all scenarios

Fig. 11. Obtained results for β = 5values

from energy exchange is a priority. In addition, purchasing from the energy pool and using bilateral contracts to cover the risk are the next priorities. In other words, a significant percentage of the consumer's purchasing portfolio is allocated to energy exchange, and the rest of the portfolio is allocated to the energy pool, while preserving the priority and using bilateral contracts. The present study has useful information based on the presented results and has high accuracy. Thus, the financial and planning managers of industries having more than five MW per month are suggested to purchase the electrical energy purchasing portfolio from electricity markets by minimizing costs and reducing risk. Furthermore, it is suggested to use other models and methods and compare the results to allocate the optimal energy purchasing portfolio in the case of uncertainty. Using other approaches to deal with uncertainty such as robust optimization, fuzzy set theory, and interval planning is suggested for future studies.

NOMENCLATURE

Indices

w	Index of periods scenario
t	Index of periods
c	Index of contracts

Sets

T	periods set at period t
C	A set of existing contracts
Z	Steps of decision tree $Z\epsilon\{1,\dots,W-1\}$
N	A set of nodes

Parameters

CT	Total expected cost of energy supply
W	List of existing scenarios in w
α	Confidence level
$P_{cw}^{c,\,min}$	Lower limit of electrical energy purchased under contract c and scenario w [KWh]
P_{tw}^{D}	The amount of electrical energy required in each scenario at time t [KWh]
CD_t	Contracts during the period t
$Sim(w,k)$	A binary matrix of scenario priority or parity
d_t	Period
P_o^D	Minimum energy demand [KWh]
λ_{tw}^{P}	The price of energy purchased from the energy pool[$]
λ_{tw}^{M}	The price of energy purchased from the electricity market[$]
π_W	Probability of scenario W
λ_{ctw}^{c}	The price of contract c for period t and scenario w [KWh]
λ_{C}^{c}	The price of contract c for the contract set C [KWh]
λ_{ctw}^{c}	Bilateral contract price purchased c in scenario w and contract period t

Variables

β	Risk factor which describes the way of thinking about risk
ξ	Maximum loss (cost) in Var (amount at risk)[$]
$P_{cw}^{c}d_t$	Energy purchased from contract c in scenario w during the contract period [KWh]
P_{tw}^{P}	Energy purchased from energy pool in scenario w at time t [KWh]
P_{tw}^{M}	Energy purchased from energy exchange in scenario w at time t [KWh]
C_{tw}^{s}	The final cost of purchasing from the instantaneous markets in scenario w and time t
S_{cw}	If contract c is selected for scenario w, it will be 1; otherwise 0
C_{cw}^{c}	The cost of purchasing from a bilateral contract in scenario w during the whole period of contract c

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