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Research paper

Portfolio management and performance improvement with Sharpe and Treynor ratios in electricity markets

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A B S T R A C T

After 1980s, liberalization in energy industry accelerated. At that times, private sector started to show more tendency to electricity thanks to regulations and policies made by governments so electricity markets emerged and spread very rapidly, which created market risk that needs to be managed carefully along. Decision makers in electricity generation industry had to be faced this market risks besides other operational risks. They had to review policies regarding to risk management and they noticed that determining the right bidding strategy for electricity market and bilateral contract market was crucial. In this paper, Mean–variance, Semi-variance, and Down-side risk methods, which are common in portfolio optimization of financial literature are used to manage risk and to optimize electricity market bidding strategies and decision policy for an electricity generation company. Apart from the other limited studies, performances of optimal portfolio solutions are measured and further more improved with the help of Sharpe and Treynor ratios for electricity market. It is seen that direct use of portfolio management tools in electricity markets can cause sub-optimal solutions, so risk aversion constant of utility functions should be adapted. This study shows that optimal bidding strategies for electricity generators can be improved with the help of Sharpe and Treynor ratios. In order to demonstrate the results, two consecutive years of Turkish Day-ahead Market data are used in an empirical case study.

1. Introduction

World primary energy need is estimated to continue increasing. According to the new policies scenario of World Energy Outlook 2015, global energy demand will increase 32% between 2015 and 2040, and 67 trillion dollars should be allocated to meet this demand (International Energy Agency, 2015). On the other hand, after Covid-19 pandemic, future projections have been changed drastically for the next five years but increase in demand will continue anyway (International Energy Agency, 2020). According to the stated policies scenario of latest published World Energy Outlook (WEO) 2020, energy demand is expected to rise by 0.9% each year to 2030 (International Energy Agency, 2020). It is updated assessment of the immediate effects of the pandemic on the energy system shows expected falls in 2020 of 5% in global energy demand, 7% in energy related CO_2 emissions and 18% in energy investment (International Energy Agency, 2020). Electricity is the very important part of this energy pool and primary energy sources (coal, natural gas, shell gas, oil, solar, wind, nuclear, hydro, geothermal etc.) are used to generate electricity. Electricity generation has great effect on environment and depending on the source it should be handled and planned carefully for effective and clean use of limited sources. Renewable resources are gaining more and more importance under the pressure of climate change, Covid-19 pandemic and Green Deal Agreement. Europe is also aiming to be the only carbon free continent in the world in 2050. According to the last report of IEA solar will be the new king of electricity and renewables meet 90% of the strong growth in global electricity demand over the next two decades (International Energy Agency, 2020).

After 1980s, liberalization in energy industry especially in electricity industry has been accelerated. One of the natural outcomes of this period was the establishment of electricity markets and the other was the disintegration with privatization in power sectors. Electricity market applications provide convenient platform for effective use of energy in such a diversified electricity environment. To provide convenient electricity market environment, deregulation of electricity industry is important and there is a remarkable tendency for restructuring of vertically integrated and heavily public owned power industry. Residual electricity energy need for grids after bilateral agreements are met by daily, hourly or fifteen minutes settled electricity markets. Deregulated electricity market application provides security of supply, grid

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stability, and merit order. Prices and market depth in spot electricity markets are indicators for stakeholders and especially for investors. There are so many stakeholders in electricity industry: generators, dispatch operators and transmission companies, retailers, regulatory authorities, consumers, industry, commercial partners, residential users etc (Gökgöz and Atmaca, 2016a). In addition to all these, electricity market brought market risk that needs to be managed carefully. To determine proper policy approaches, decision makers in electricity industry should have to be faced with this market risk besides other operational risks. So proper risk management approaches should be used by decision makers to control risks arising from electricity markets. Additionally, the implications of the pandemic and economic slump are significant, particularly in some emerging markets and developing economies (International Energy Agency, 2020).

Portfolio optimization is one of the methods that can be used for risk management and together with its derivatives are widely used in financial literature but there are still limited studies in electricity markets (Atmaca, 2017; Garcia et al., 2017). It is based on the tradeoff between risk and return. Before 1950, classical portfolio theory was widely accepted by investors but it was not systematic (Statman, 1987; Jones, 2000; Copeland et al., 2005). According to classical portfolio approach, the risk of portfolio declines and converge to market risk as more and more securities added. After that, in 1952, Modern Portfolio Theory (MPT) was introduced to financial literature by Markowitz: it demonstrated that the classical theory did not have a systematic approach because it only concentrated on number of assets without taken into consideration co-movement of assets (Markowitz, 1952; Sharpe et al., 1999). The presence of correlation between assets decreases the positive effect of diversification and causes to produce less effective portfolios (Liu and Wu, 2006). MPT is based on mean variance, and the maximization of return for a given level of risk or minimization of risk for a given level of return, in this way by taking into account correlation between assets, it produces efficient frontier (Gökgöz and Atmaca, 2012; Liu et al., 2006). Sharpe and Linther improved a theory later on separately in 1964–1965, and capital asset pricing model (CAPM) was introduced to financial literature in this way (Sharpe, 1964; Linther, 1965a,b).

There are so many other methods derived from MPT approach later on: Semi-variance and Down-side risk methods are two of them. While MPT is concentrating on both negative and positive deviations from expected returns, above mentioned approaches consider only negative deviations from expected returns. Semi-variance and Down-side risk are special cases of Bernell Stones' Generalized Risk Measure and they are called as second and first order Lower Partial Moments (LPM) respectively: Semi-variance is taking into account the square of negative deviations from target return while down-side risk includes directly negative deviations from target return (Gökgöz and Atmaca, 2017a; Roy, 1950; Yu, 2007).

In the literature before 2003, various risk management methodologies have been applied to electricity markets. Hedging of spot market price risk with the help of forward contracts are the frontier studies (Kaye et al., 1990; Gedra, 1994; Gedra and Varaiya, 1993). Application of future contracts and other derivative products have also been considered (Collins, 2002; Bjorgan et al., 1999; Tanlapco et al., 2002). Monte Carlo and decision analysis have been applied to find optimal contract shares (Vehviläinen and Keppo, 2003; Sheblé, 1999; Kumar and Sheblé, 1996; Siddiqi, 2000). After 2000s, it seems that Mean–variance is the most used method, on the other hand, Value-at-risk (VaR), Conditional Value-at-risk (CVaR), Sharpe ratio, Down-side risk, Semi-variance, CAPM, Variance, Mean variance-skewness, and Monte Carlo are the other preferred techniques (Atmaca, 2017; Garcia et al., 2017). VaR has been implemented in electricity markets (Dahlgren et al., 2003; Liu and Wu, 2007b). Allocation of energy between spot and contract market by using mean variance has been studied (Liu and Wu, 2007a). Forecasting of prices and consideration of covariance between spot markets have been also studied (Mathuria and Bhakar, 2014). Using of Markowitz' mean variance to determine portfolio weights of spot hours and bilateral contract market for different generation technologies has been studied for Turkish Electricity Market (Gökgöz and Atmaca, 2012). Mean–variance skewness model has been studied for PJM markets (Pindoriya et al., 2010). Wnag et al. used VaR and CVaR for four markets (Wang et al., 2005). CVaR was also used by Mehranfar with four trading strategies and he showed the clear trade-off relationship between risk and profit (Mehranfar, 2020). Garcia et al. used mean variance criterion (MVC) and CVaR combined with GARCH model in PJM Market (Garcia et al., 2017). Mean–variance together with machine learning was also used for portfolio optimization via stock price prediction (Chen et al., 2021). Lower partial moments have been studied to determine optimal portfolio solutions for generation operators (Gökgöz and Atmaca, 2017b). PJM, Nordic and Turkish electricity markets are heavily studied electricity markets in the field.

This paper aims to make contribution to limited number of portfolio optimization studies in electricity markets and to provide proper risk management techniques for decision makers and other stakeholders in electricity markets. To the best of author knowledge, the study of Sharpe ratio together with Treynor ratio to measure and improve the performance of portfolio in electricity market has not been studied yet. Mean–variance, Semi-variance, and Down-side risk methods are simultaneously used for portfolio optimization results. Sharpe and Treynor Ratios are additionally applied for not only performance measurement but also for performance improvement. Performance of optimal portfolios are analyzed based on different risk aversion levels of investors. Optimal risk aversion constants for investors' utility functions are determined for Turkish day-ahead electricity market. By using this approach, an electricity generation utility can determine suitable selling policy and improve its bidding strategy in the spot electricity markets.

Next sections are organized as follows: Section 2 introduces a short theoretical background of portfolio optimization theory including MPT, Sharpe, and Treynor ratios. Section 3 demonstrates the current situation of Turkish day-ahead electricity market. Section 4 introduces data and research method. Section 5 provides a case study and the results of this case study based on methods demonstrated in this paper. And finally, Section 6 discusses and concludes these results.

2. Portfolio optimization theory

2.1. Markowitz mean–variance analysis

Markowitz Mean–variance analysis or MPT is a mathematical framework for establishing a portfolio from risky assets. The expected return of portfolio is maximized for a given level of risk, which is defined as standard deviation or variance. Contrary to Classical Portfolio Theory, MPT takes into account correlations between risky assets, which provides to constitute less risky portfolios than portfolios being established by ignoring correlation of risky assets (Atmaca, 2017; Liu and Wu, 2006).

Markowitz, who introduced MPT to the finance literature, published a paper "Portfolio Selection" in 1952 for the first time (Markowitz, 1952). Markowitz was awarded the Nobel Prize thanks to his work on portfolio theory. Markowitz, in his famous article, argued that portfolio selection can be divided into two steps: the first stage starts with the evaluation of the future performance of securities and ends with beliefs, second stage ends with portfolio selection (Markowitz, 1952). Later on, with the addition of a risk-free asset, Sharpe and Linther improved a capital market line that has a point of tangent to efficient frontier and introduced CAPM to literature separately (Cohen and Natoli, 2003). The details of MPT and CAPM are discussed and can be seen in many studies (Atmaca, 2010, 2017; Copeland et al., 2005; Markowitz, 1952, 1959; Sharpe, 1964; Linther, 1965a; Sheblé, 1999; Gökgöz and Atmaca, 2013, 2016b).

Markowitz's portfolio theory is based on mean–variance. It looks for efficient portfolios that provide minimum achievable risk for a predetermined level of return or maximum rate of return for a given level of risk (LeCompte, 2008). Assumptions of the theory are listed as follows:

- No transaction costs, commission fee or taxes,
- All investors are in risk averse position, they prefer less risk for the same level of expected returns and more expected return for the same level of risk,
- Investors or electricity generation companies have all information regarding the expected returns, variances, and co-variances of all risky assets. There is no asymmetric information distribution,
- While taking investment decisions, investors consider only expected returns, variances, and co-variances of risky assets,
- Expected returns of assets have normal distribution.

If the returns of assets obey with the normal distribution, then the possible distribution of the alternative portfolios can be described by using their means and variances only (Levy and Post, 2005).

Mean–variance optimization methodology for n risky assets includes three fundamental constraints:

- The sum of risky assets' weights is equal to 1.
- Non-negativity for assets' weight
- Expected return of portfolio is equal to target return

Equation set for mean–variance optimization with n risky assets are formed as follows:

$$Min.\left(\sigma_p^2\right) = \sum_{i=1}^{n}\sum_{j=1}^{n} x_i x_j \sigma_{ij} \tag{1}$$

s.t.

$$\sum_{i=1}^{n} x_i r_i = r_{target} \tag{2}$$

$$\sum_{i=1}^{n} x_i = 1 \tag{3}$$

$$x_i \geq 0, \forall x_i \in i = [1, 2, \ldots, n] \tag{4}$$

$$\sigma_{ij} = \frac{1}{K-1}\sum_{m=1}^{K}\left(r_{i,m} - \overline{r_i}\right)\left(r_{j,m} - \overline{r_j}\right) \tag{5}$$

where n is the number of risky assets in the portfolio, x_i are decision variables and denote the weight percentages of ith asset, r_i denotes expected average return of ith asset, σ_{ij} shows the co-variance between ith and jth asset. According to Markowitz mean variance approach, the solution of this optimization problem for different target returns produces an efficient frontier as shown in Fig. 1. To reach the optimal portfolio solution, utility functions are used. Utility functions include the investor's risk and return expectation. Utility function for this problem is determined in a quadratic form and it includes a constant that represents investors' risk aversion level (Gökgöz and Atmaca, 2016a). The value of utility function for investors never changes along this utility curve. The tangent point between utility function and efficient frontier determines optimal market portfolio solution and it also represents the market portfolio as shown in Fig. 1. First equation set (1–5) is used to generate efficient frontier and second equation set (6–8) is used for the utility function to reach optimal portfolio on this efficient frontier. They both have the same decision variables but they are not solved simultaneously. First, the efficient frontier then utility function set are solved. This is also valid for down-side and semi-variance analysis cases.

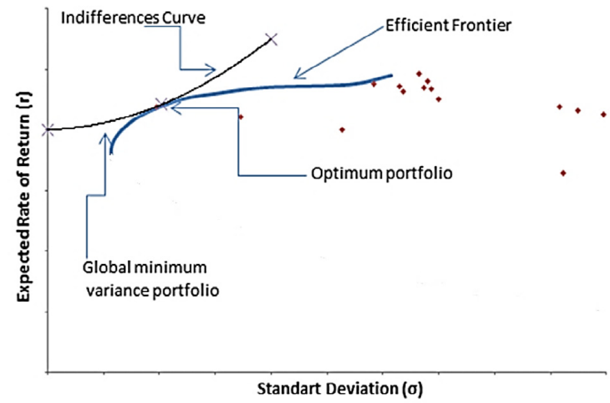

Fig. 1. Efficient frontier and utility function.

Utility function U seen in Fig. 1, is a quadratic form and it includes the terms expected return of portfolio $E(r_p)$, risk of portfolio σ_p^2, and constant A that represents the risk aversion level of investor where x_i are decision variables and denote the weight percentages of ith asset. It is used in the same quadratic form like in finance and electricity market optimization applications (Atmaca, 2017; King, 2007). The portfolio that gives the maximum value of utility function is a maximization problem and obtained as follows:

$$Max.\,(U) = E\left(r_p\right) - 1/2A\sigma_p^2 \tag{6}$$

s.t.

$$\sum_{i=1}^{n} x_i = 1 \tag{7}$$

$$x_i \geq 0, \forall x_i \in i = [1, 2, \ldots, n] \tag{8}$$

There are other studies that configure problems with adding of risk-free asset, fixed price asset, customizing upper and lower investment constraints for each of risky assets, lending and borrowing and so many other issues (Liu and Wu, 2006, 2007a,b; Gökgöz and Atmaca, 2012, 2013, 2017b).

2.2. First degree lower partial moment or down-side analysis

Down-side risk is defined as the first order lower partial moment. It takes into account only the first order of negative deviations from target return (Grootveld and Hallerbach, 1999). As a first order LPM_1, down-side risk is formulized as follows:

$$LPM_1\,(\tau : r) = \int_{-\infty}^{\tau} (\tau - r)\, dF(r) \tag{9}$$

Where τ represents target return value and $F(r)$ represents cumulative distribution function. Solution of equation set for down-side risk provides an efficient frontier. Equation set for down-side optimization with n risky assets is formed as follows:

$$Min.\sum_{j=1}^{M} p_j(d_j^-) \tag{10}$$

s.t.

$$\sum_{i=1}^{n} x_i = 1 \tag{11}$$

$$\sum_{i=1}^{n} x_j r_{ij} = r_j, \forall r_j \in [j = 1, 2, \ldots, M] \tag{12}$$

$$\sum_{j=1}^{M} p_j r_j = r_{target} \tag{13}$$

$$d_j^- = \max[0, -\left(r_j - r_{target}\right)] \tag{14}$$

$$x_i \geq 0, \forall x_i \in i = [1, 2, \ldots, n] \tag{15}$$

Where M describes the number of scenarios, p_j denotes the probability of jth scenarios, d_j^- indicates negative deviation of jth scenarios from target returns, and x_i are decision variables and denote the weight percentages of ith asset. Utility function for down-side risk analysis is formed as follows (Gökgöz and Atmaca, 2012):

$$Max.\,(U_{DS}) = E\left(r_p\right) - 1/2ALPM_1\,(\tau : r) \tag{16}$$

s.t.

$$\sum_{i=1}^{n} x_i = 1 \tag{17}$$

$$x_i \geq 0, \forall x_i \in i = [1, 2, \ldots, n] \tag{18}$$

2.3. Second degree lower partial moment or semi-variance analysis

Semi-variance is another special form of lower partial moment. It uses square of negative deviations from the target return so it is called as second order/moment (Grootveld and Hallerbach, 1999; Gökgöz and Atmaca, 2013). Semi-variance is formulized in the following form:

$$Min.\sum_{j=1}^{M} p_j \left(d_j^-\right)^2 \tag{19}$$

s.t.

$$\sum_{i=1}^{n} x_i = 1 \tag{20}$$

$$\sum_{i=1}^{n} x_j r_{ij} = r_j, \forall r_j \in [j = 1, 2, \ldots, M] \tag{21}$$

$$\sum_{j=1}^{M} p_j r_j = r_{target} \tag{22}$$

$$d_j^- = \max[0, -\left(r_j - r_{target}\right)] \tag{23}$$

$$x_i \geq 0, \forall x_i \in i = [1, 2, \ldots, n] \tag{24}$$

Object function of Semi-variance model is different from down-side but the other constraints and decision variables are the same. As a second order of LPM_2, Semi-variance uses square of left-hand side deviations and LPM_2 for semi-variance is formulized as follows (Gökgöz and Atmaca, 2017a).

$$LPM_2\,(\tau : r) = \int_{-\infty}^{\tau} (\tau - r)^2\, dF(r) \tag{25}$$

Depending on the risk aversion level of investor, utility function should be maximized to reach optimal portfolio solutions (Donghan et al., 2007). Utility function of Semi-variance is formed as follows:

$$Max.\,(U_{SV}) = E\left(r_p\right) - 1/2ALPM_2\,(\tau : r) \tag{26}$$

s.t.

$$\sum_{i=1}^{n} x_i = 1 \tag{27}$$

$$x_i \geq 0, \forall x_i \in i = [1, 2, \ldots, n] \tag{28}$$

2.4. Performance measurement: Sharpe and Treynor ratio

Indeed, there are many performance measurement approaches for portfolio performance measurement in finance: Sharpe Ratio (reward to variability), Treynor Ratio (reward to volatility), Sortino Ratio, Information Ratio *IR*, Jensen alpha, and Omega etc (Karan, 2004). Sharpe and Treynor are the most common in finance but to the best of author knowledge there is no other study dealing with portfolio optimization in electricity market with using Sharpe and Treynor together so in this study these two performance measurements are preferred to measure and improve the performance of portfolios.

Sharpe Ratio is a well-known performance indicator and it is widely used in financial literature. It is called as reward to variability and it is one parameter measurement method which includes residual return (the difference between portfolio return-r_p and risk-free return r_f) and risk (standard deviation of portfolio σ_p) (Gökgöz and Atmaca, 2016a). Sharpe Ratio is calculated by division of residual return by risk of portfolio as follows:

$$SharpeRatio(RVAP_p) = (r_p - r_f)/\sigma_p \tag{29}$$

Treynor Ratio is the other important and well known performance indicator in financial literature. Treynor is called as reward to volatility and it is again one parameter measurement method. It includes residual return and beta (β) constant (Karan, 2004). β is a constant as seen below, it is calculated with the help of an index or benchmark portfolio. Treynor Ratio is calculated by division of residual return by beta of portfolio as follows:

$$\beta = Cov(i, m)/\sigma_m^2 \tag{30}$$

$$TreynorRatio(RVOL_p) = (r_p - r_f)/\beta \tag{31}$$

3. Electricity in Turkey and electricity market structure

Turkey with 83 million population is a developing country. It is listed in the 20 biggest economy in the world (actually in 19th row in 2019), and it is also a member of OECD (World Bank, 2020). Population and economic growths are relatively high respect to world average and Europe. It has very young population. Turkey has also important location between Asia and Europe and is seen as an energy corridor between Middle East, Russia, Caucasia, and Europe (Atmaca, 2017).

Turkish electricity industry goes back to 1902 (Öztürk et al., 2007). The first electricity company of Turkey was established in Kayseri in 1926 (Çolak et al., 2014; Bağdadioğlu and Ödyakmaz, 2009). Installed capacity of Turkey reached about only 408 MW at the beginning of 1950s and the total annual generation was only about 790 GWh (Öztürk et al., 2007). There was vertically integrated structure and public ownership in the electricity industry. It continued till 1984, when a reform programme for liberalization and incentives of electricity was initiated (Atmaca, 2017). In 1993 vertically integrated public electricity utility TEK was divided into two separate companies: Turkish Electricity Generation and Transmission Co. (TEAS) and Turkish Electricity Distribution Co. (TEDAS) (Gökgöz and Atmaca, 2013). Energy Market Law (No. 4628) entered into force and electricity generation was separated from TEAS in 2001 and the reform programme gained momentum in Turkey (Atmaca, 2010). In 2013, New Electricity Market Law number 6446 entered into force and most of the terms of 4628 were abolished or changed. From 1975 to 2013, installed capacity of electricity portfolio was risen by 7.44% each year (Gökgöz and Atmaca, 2017b). Between 2001 and 2020, step by step: balanced market, day-ahead planning, day-ahead market, intraday market, and derivative markets for electricity were implemented (Atmaca, 2017). At the end of August 2021, total installed capacity of Turkey has reached 98493 MW (TEIAŞ, 2021).

In Turkish day-ahead spot electricity market, market members can tender hourly, flexible, and block (at least 4 consecutive hours) offers. Hourly and block tenders take priority regarding to flexible offers (Gökgöz and Atmaca, 2016b). In day-ahead spot electricity market, all offers are gathered for 24 h of next day, just 11–35 h before real market time (Atmaca, 2017). All bids and demands are gathered and one uniform price is determined for system clearing price for market. This price is applied to all market participants and clearing house guarantees the payments. Additionally, an intra-day market mechanism is operated, market players can give their bids for this market just 90 min before the real time operation. Intra-day mechanism acts as a second chance for market players to balance their obligations (EMRA, 2017). There are hourly balanced market, capacity market and auxiliary market structures, too. Furthermore, future market has been operational since the end of June (EPİAŞ, 2021).

4. Data and methodology

Within the scope of this study, Turkish day-ahead market hourly weekdays' prices of two consecutive years, between 2014, April 28 and 2016, April 24, are taken into account for application (EXIST, 2021). Total size of hourly prices data used in this study are 12480. Data includes prices of 24 h of 520 weekdays. The consumption behaviors at weekends are very different from weekdays so as mentioned in assumptions, so only weekdays are taken into consideration in this study. Day-ahead electricity market trades with Turkish Lira. All price data has been converted from Turkish Lira to Euros by using daily exchange rates of TCMB (Central Bank of The Republic of Turkey).

Unlike the stock markets, market clearing prices of electricity market are very volatile as seen in Fig. 2. So the range of returns are relatively high and volatile in electricity markets. And rates of return are normalized with the generation costs of electricity. Depending on generation cost, rates of return can change a lot. Approaches which are previously studied and experienced are used in this normalization process (Atmaca, 2017; Gökgöz and Atmaca, 2017a,b; Liu and Wu, 2007a); Normalization is done in accordance with the following formulas:

$$r_{n,m} = (A_{n,m} - C)/C(m = 1, 2, \ldots, 520) \tag{32}$$

$$\vec{r_n}^{\,t} = \begin{bmatrix} r_{n,1} & r_{n,2}\ldots & r_{n,m} \end{bmatrix} (n = 1, 2, \ldots, 24) \tag{33}$$

Where n indicates 24 h of a day, m indicates sample size of data, C shows average generation cost of unit for given period of time. In this study C is assumed as 10 €/MWh and not changed during the calculation period. Because of the fact that electricity generation cost data is assumed as commercially sensitive information, a representative constant number is assumed as a generation cost in this study. $A_{n,m}$ represents hourly electricity market prices of nth hour of mth day. $r_{n,m}$ indicates rate of return normalized with electricity generation cost and finally $\vec{r_n}^{\,t}$ is shown transpose of return vector. Risky assets based on given cost level are formed as in Table 1.

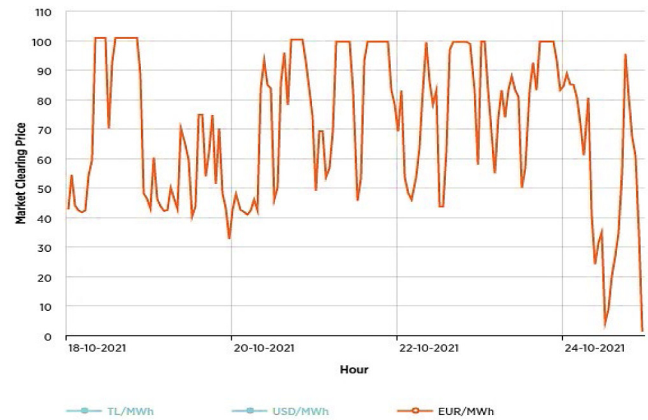

Fig. 2. Volatility of market clearing prices for one-week period.

5. Results

In general, capacity factors of hydropower plants are heavily rely on climate conditions. They are not assumed as base load power plants. The production programme of a hydropower plant is effected from seasonal periods, geographical and weather conditions. Average capacity factor of a hydropower plant in Turkey is generally between 30% and 50%. On the other hand, 100% capacity factors can be reached depending on the reservoir capacity of related power plant for a limited period of time.

Within the scope of this study it is assumed an electricity generator (GenCo) has a 100 MWe hydraulic power plant with one unit and is being operated in Turkey. GenCo has a bilateral contract to sell 40% of its capacity. And according to production programme, GenCo is trying to sell remaining part of electricity (for 24 h) in the day-ahead market for the next day. This study is searching for the answer of what the best-selling strategy should be for next day day-ahead market under above mentioned assumptions. The parameters and constraints are introduced in Table 2.

As seen in Table 2, three optimization methods are applied for portfolio selection problem and two performance measurement ratios are used to measure and improve performance of the solutions. Each hour of 24 h of a day in electricity market is assumed as a separate risky asset. Main assumptions not listed in Table 2 for this case study are listed below in the following form:

- Market has enough monetary depth.
- Bids can be divided into infinitesimal parts.
- All bids will be sold in the electricity market.
- GenCo is a rational company and prefers highest expected return for the same level of risk, and lowest risk for the same level of expected return.
- Availability of generation unit is 100% at full power.
- Rates of return have normal distribution.
- There is not any congestion to limit grid.
- There is no water income limitation. There is enough water in reservoir.
- Generation unit has flexibility to operate every level of generation between 40% and 100%.
- There is no efficiency loss due to operation intervals or reservoir level.

Return vectors of 24 risky assets with 520 elements in each vector were produced and related covariance matrix (24 × 24) was created to use in mean–variance analysis. Mathematical

Table 1
Risky assets for hydraulic power plant.

Risky asset	Mean return	Std. deviation	Risky asset	Mean return	Std. deviation
Hour-1	3.8394	1.3385	Hour-13	4.6246	1.4241
Hour-2	3.2769	1.4910	Hour-14	4.8311	1.3113
Hour-3	2.6752	1.6003	Hour-15	4.9958	1.2502
Hour-4	2.1943	1.6485	Hour-16	4.8964	1.2678
Hour-5	2.1158	1.5927	Hour-17	4.8726	1.2959
Hour-6	2.2296	1.4979	Hour-18	4.6334	1.4586
Hour-7	2.5424	1.5344	Hour-19	4.3858	1.3630
Hour-8	3.5312	1.3203	Hour-20	4.2689	1.2581
Hour-9	4.6370	1.2668	Hour-21	4.2196	1.2047
Hour-10	5.1343	1.1394	Hour-22	3.9885	1.3017
Hour-11	5.1721	1.1779	Hour-23	4.0395	1.3760
Hour-12	5.1977	1.1344	Hour-24	3.5993	1.5371

Table 2
Case study data and constraints for Turkish electricity market.

Topic	Case value
Installed capacity	100 MWe
Bilateral contract share	40 MWe
Total available energy	500 MWh
Investment period	1 weekday
Generation cost	10 €/MWh
Bilateral contract price	25 €/MWh
Weekdays	Mon. Tue. Wed. Thu. Fri.
Market Data	Turkish day-ahead spot prices between 28th April, 2014/ 24th April 2016
Number of risky assets	24
Upper investment constraints	12%[a]
Portfolio optimization methods	Mean–variance, Semi-variance, Down-side
Performance measurement methods	Sharpe Ratio, Treynor Ratio
Benchmark portfolio	12% of 9, 10, 11, 12, 14, 15, 16, and 17th hours and 4% of 18th hour (most expensive hours)

[a] 12% upper investment limit comes from division of residual power for one hour (60 MWe) to total available energy (500 MWh). It describes the maximum amount of electricity that can be sold in one hour which is equal to 60 MWh or 12% of total available energy.

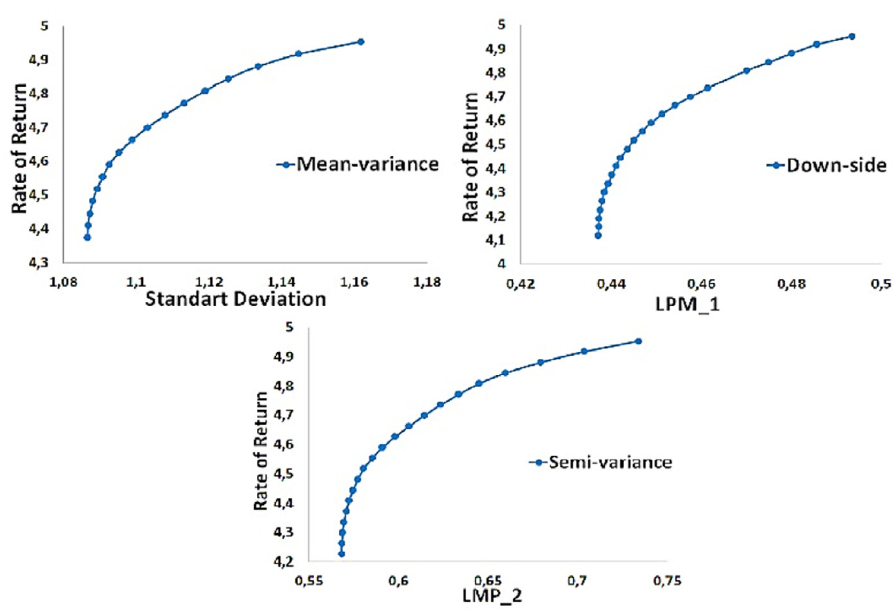

Fig. 3. Efficient frontier for optimization methods based on their respective risks.

models of mean–variance, down-side, and semi-variance methods were prepared in line with Section 2. The results of analysis for three models were obtained by using MatLab. Efficient frontier results are demonstrated in Fig. 3 for all optimization methods.

All efficient frontiers show the same behavior independent from the method as it is expected. All optimal portfolios on efficient frontiers have minimum relative risk for a given level of return or maximum return for a given level of related risk. When Sharpe ratio and Treynor ratio performance indicators of efficient frontier portfolios are measured and analyzed separately, it has been seen that Sharpe and Treynor ratios provide maximum performance values at some point on efficient frontiers as seen

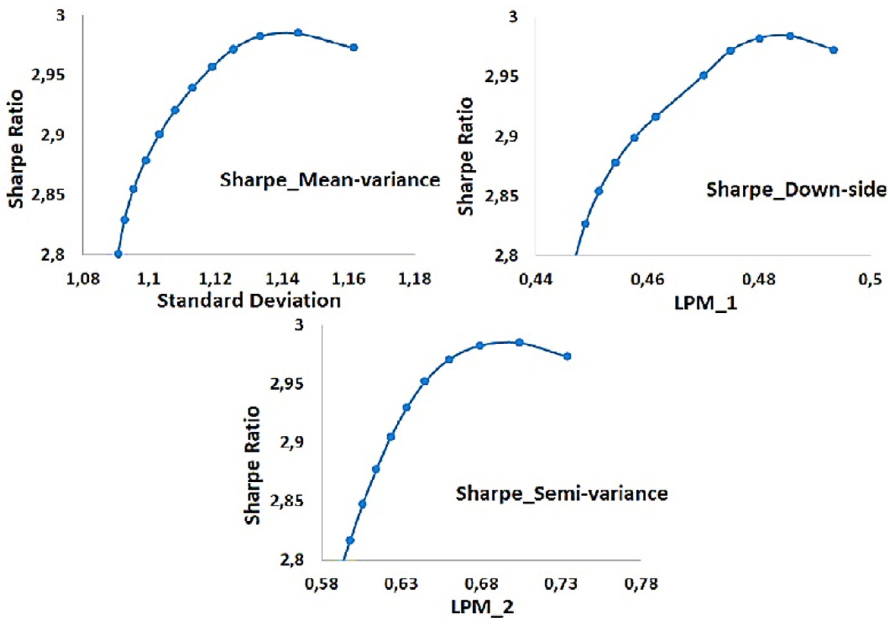

Fig. 4. Sharpe ratio performances of efficient frontier portfolios.

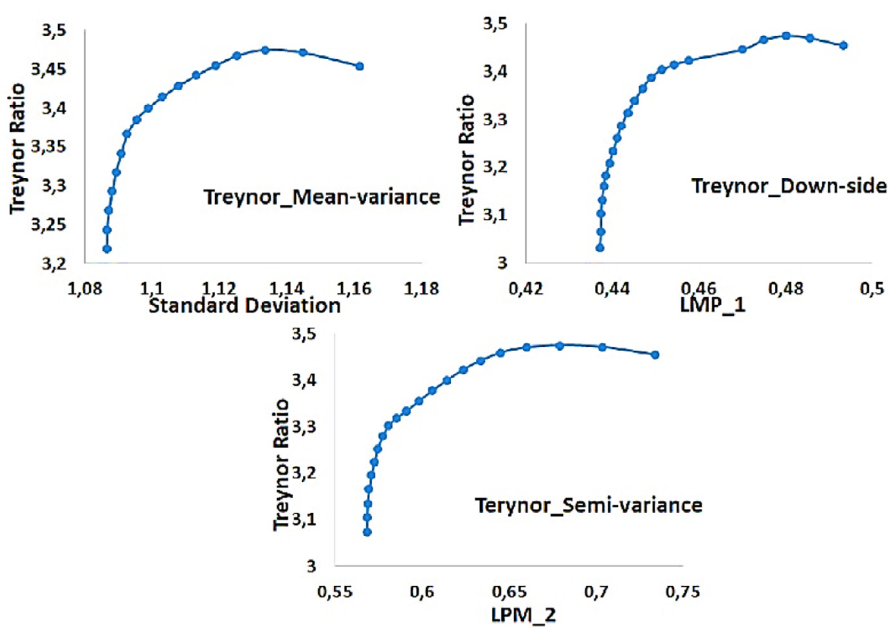

Fig. 5. Treynor ratio performances of efficient frontier portfolios.

in Figs. 4 and 5. So the decision makers should take into consideration this fact to determine the best Sharpe and/or Treynor portfolios.

Decision makers' utility functions for each methodology, which are described in Eqs. (6), (16), and (26), include a term A that shows the risk aversion level of decision maker. The higher values of A are more suitable for risk averse decision makers (Atmaca, 2010). In finance, A is generally assumed as 3 for neutral risk averse decision makers, with the rise of risk aversion level, A goes up (Sharpe et al., 1999; Karan, 2004). Risk seeking decision makers prefer A to be less than 3 while risk averse decision makers prefer A to be more than 3 (Liu and Wu, 2007a). In Fig. 6, Sharpe and Treynor performance measurement of optimal portfolios obtained for different levels of A between 0 and 15 are demonstrated.

According to the case study, in each method, Sharpe and Treynor ratios are maximized for different values of A. Sharpe ratios reached their maximum values in mean–variance analysis for the values of A between 1.5 and 4.0, in down-side risk analysis for the values of A between 7.0 and 13.5, and in semi-variance for the values of A between 2.5 and 4.0. These results are different from the other studies using the same data set (Gökgöz and Atmaca, 2016a). It is seen that each case is idiosyncratic. Rather than directly using the results of this study, decision makers customize and adapt their cases to use these optimization and performance measurement methods. To reach optimal solution, tuning is important. As to Treynor ratios for different optimization methods, they reach their maximum values in mean–variance analysis for the values of A between 1.5 and 4.0, in down-side risk analysis for

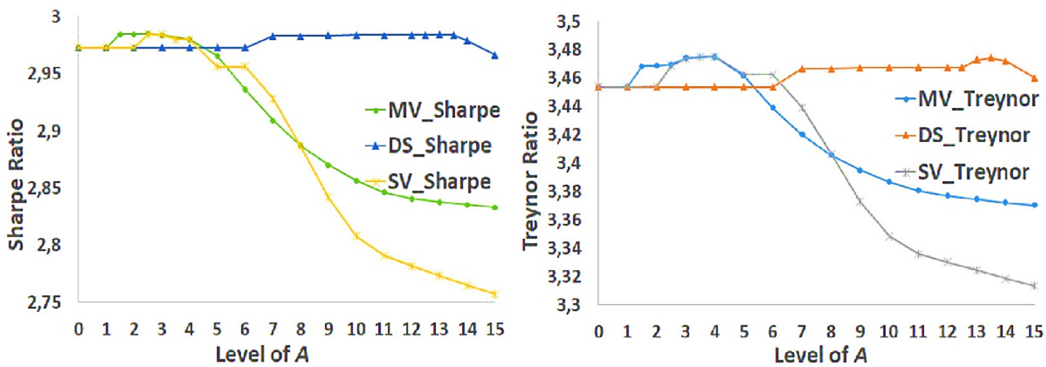

Fig. 6. Sharpe and Treynor ratios for different risk aversion levels.

Table 3
Sharpe and Treynor optimum portfolio solutions for optimization methods.

Hour	Sharpe optimum (%)			Treynor optimum (%)		
	Mean–variance (MV)	Down-side (DS)	Semi-variance (SV)	Mean–variance (MV)	Down-side (DS)	Semi-variance (SV)
8	0.00	0.01	0.00	0.00	0.00	0.00
9	12.00	12.00	12.00	12.00	12.00	12.00
10	12.00	12.00	12.00	12.00	12.00	12.00
11	12.00	12.00	12.00	12.00	12.00	12.00
12	12.00	12.00	12.00	12.00	12.00	12.00
14	10.52	5.25	12.00	0.00	4.00	0.00
15	12.00	12.00	12.00	12.00	12.00	12.00
16	12.00	11.99	12.00	12.00	12.00	12.00
17	12.00	11.99	12.00	12.00	12.00	12.00
20	0.00	0.44	0.00	4.00	0.00	4.00
21	5.48	10.29	4.00	12.00	12.00	12.00

Table 4
Sharpe and Treynor optimum portfolio's performance values and related risk aversion constants.

Constant	Sharpe optimum			Treynor optimum		
	Mean–variance (MV)	Down-side (DS)	Semi-variance (SV)	Mean–variance (MV)	Down-side (DS)	Semi-variance (SV)
A	2.5	13.0	2.5	4.0	13.5	3.5
r_f	1.5	1.5	1.5	1.5	1.5	1.5
r_p	4.9282	4.89594	4.93728	4.86578	4.88833	4.86584
r_m	4.95379	4.95379	4.95379	4.95379	4.95379	4.95379
σ_p	1.14845	1.13794	1.15165	1.12947	1.13553	1.12948
β	n.a.	n.a.	n.a.	0.9685	0.9752	0.9685
Performance	2.9851	2.9843	2.9846	3.4753	3.4745	3.4753

the values of A between 7.0 and 14.0, and semi-variance for the values of A between 2.5 and 4.0. In Table 3, results of all Sharpe and Treynor optimum portfolios are demonstrated. Weighting factors of optimal portfolios are obtained with the solutions of utility functions demonstrated in Eqs. (6), (16), and (26) according to A values which maximize the Sharpe and Treynor. Investor can use weighting factors obtained from solutions as a bidding strategy for electricity market.

According to Table 3, 9th, 10th, 11th, 12th, 15th, 16th, and 17th hours are common in solutions and they are in the upper limit. 21st hour is only common in Treynor optimum solutions with being in the upper limit. 14th and 20th hours are changing in results depending on methods. 8th hour is ignorable. Independent from methodology, all methods have produced very close portfolio solutions and two of them are the same. As to performance, Table 4 introduced the performance values of optimum portfolios and their related risk aversion constant of decision makers. Depending on the methods, it is possible to achieve same performances for Sharpe and Treynor ratios but investor risk aversion constant A should be adjusted as seen in Table 4 otherwise there is a possibility to reach sub-optimal portfolios.

6. Conclusion

In this study, Mean–variance, Down-side, and Semi-variance portfolio optimization methods are successfully applied to two consecutive years' data of Turkish day-ahead electricity market. Risk management through diversification is shown by using different optimization methods widely used in financial literature but limited in electricity markets optimization.

Efficient frontiers, utility functions and related optimal portfolio solutions are obtained for each optimization methodology. The performance of efficient frontiers and optimal portfolios solutions are measured as seen in Figs. 4 and 5. To the best of author knowledge, for the first time effective intervals of optimum risk aversion constants A of decision makers' utility functions that maximize Sharpe and Treynor ratios have been studied, were determined and compared as seen in Fig. 6. Sharpe and Treynor ratios are performance measurement metrics to measure performance of portfolios. Achieving the highest Sharpe ratio or Treynor ratio value means finding the best performing portfolio. Maximum value of Sharpe ratio was calculated as 2.9851 and maximum value of Treynor ratio was calculated as 3.4753. Sharpe ratios reached their maximum values in mean–variance analysis for the values of A between 1.5 and 4.0, in down-side risk between 7.0 and 13.5, and in semi-variance between 2.5 and 4.0. Treynor ratios for different optimization methods reached their maximum values in mean–variance analysis for the values of *A* between 1.5 and 4.0, in down-side risk analysis between 7.0 and 14.0, and semi-variance between 2.5 and 4.0. It is understood that Sharpe and Treynor ratios can be used to improve mean–variance, down-side risk and semi-variance portfolio optimization approaches.

For Turkish day-ahead electricity market, very similar portfolio optimization results were obtained for Sharpe and Treynor optimum solutions. Solutions improved from these two methods are supporting each other. According to Table 3, 9th, 10th, 11th, 12th, 15th, 16th, and 17th hours are common in solutions of two methods and they are in the upper limit of 12%.

Additionally, it is understood that independent from the optimization methods, same or very similar Sharpe or Treynor optimum portfolios can be obtained by correctly adjusting risk aversion constants to reach right solutions. Decision makers should customize their risk aversion constants of related utility functions according to optimization method. Otherwise sub-optimal, sub-performed solutions can be obtained. These can be seen in the performance results of portfolios. There is a transitivity among methods with the tuning of utility functions. While determining the policy for bidding strategy in electricity markets, instead of direct use of financial methods, it should be carefully evaluated financial factors and effective range of them for portfolio selection problems.

The main contributions and novelty of this paper can be summarized as: To the best of author knowledge, this is the first study to measure and improve the performance of portfolio in electricity market by using Sharpe ratio together with Treynor ratio. Moreover, effective intervals of optimum risk aversion constants *A* of decision makers' utility functions that maximize Sharpe and Treynor ratios have been studied, determined and compared for electricity markets for the first time.

Finally, as to future directions, this study can be extended in ways that includes other performance measurement methods like Jensen, Information Ratio, Omega or Sortino and the results can be compared. Changing of upper investment limits and addition of risk free asset (fixed price bilateral contracts for electricity markets) can also be taken into consideration to make diversification. Changing of optimal portfolio solutions and performance measurement of them based on different time period intervals can also be applied. Different type of electricity generation portfolios can be constructed by including natural gas, coal, renewable, nuclear, wind, solar and battery etc. Conducting the same study for two different electricity market and comparison of solutions are other alternative potential studies.

CRediT authorship contribution statement

Mete Emin Atmaca: Conceptualization, Methodology, Software, Formal analysis, Data curation, Writing, Visualization, Project administration, Validation.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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