Modeling, Planning and Evaluating the Investment Risk of Multiple Energy Centers Based on the Estimation of Data

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In this paper, we proposed a financial evaluation method for energy centers with the ability to convert and manage the selection of the type of exhaust fuels. An energy center is an integrated system, for example, a power unit that convert or store multiple energy carriers. Given the flexibility of energy centers to change their output power (s), as well as the uncertainties in some parameters such as the price of energy carriers, inflation, consumption, etc., the value of its investment is uncertain and based on The Monte Carlo simulation is determined. By the Monte Carlo method and the Hull-White-Vasicek method, the price of energy carriers will be estimated in the coming days using data from previous years. This approach has been the ability to adapt flexibly to uncertain and volatile market prices. The estimated price error is shown using the above methods and real data. Then, the model of the proposed energy center is determined by the size of the risk and its profitability. © 2018 Journal of Energy Management and Technology

keywords: *Energy Center, HWV method, Simulation of Monte Carlo, Multiple energy carriers, Power generation investment, investment risk.*

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NOMENCLATURE

A. Indices:

P **to** P_w Input energy of energy center

L **to** L_w Energy outputs of energy center

R Discount factor

S Net income

N Life of the project

X Normal distribution function

U_1 Random numbers

U_2 Random numbers

Ω correlation matrix

Δz Random variable with a normal distribution

Δt Variance of normal distribution

H Hour (time period)

E Error vector

A Average return

μ Average value of x in the long run

$\sum$ Price instability

χ Natural logarithm of the price of the energy carrier

Q Delay factor

1. INTRODUCTION

Most studies have been on the analysis of simultaneous production systems involving several input carriers [1–5]. In this research, production resources and technologies such as synchronous power that underpin their ability to produce several different energies have a special significance for the development of these studies. The integrated monitoring of multiple energy carriers as inputs and outputs allows the identification of unused capacities to improve the system, including increasing energy efficiency and increasing profits from product sales.

The picture of the energy center is shown in Fig. 1 An energy center can provide a specific energy carrier with multiple input energy carriers or systems. For example, the energy center of Figure 1 can provide its own thermal load via CHP or boiler. This abundance allows the functionality and outputs of the center to be adapted to a decision-making environment with variables such as prices or loads.

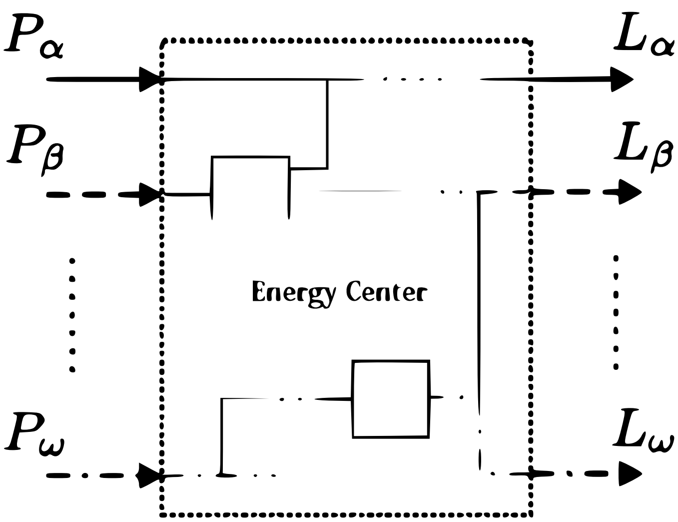

Fig. 1. Example of an energy center, P to Pw, input energy and L to Lw are the energy outputs of the energy center

The purpose of this paper and research provided an investment valuation method in the energy center that takes into account the types of energy flux in it. Using Monte Carlo simulation, flexibility is considered to be responsive to variable market prices and temperatures [6]. Different from definitive models, the Monte Carlo method uses random models to illustrate these sources of uncertainty that can have a potential impact on the value of capital.

However, Monte Carlo method has been used to analyze the investment of synthetic power plants [7]- [9]. The model presented in this paper, in addition to the generalization of the Monte Carlo evaluation method for the number of arbitrary inputs and outputs energy carriers, is presented in energy centers, pricing parameters for years to come using past years' data and obtained by the Hull-White-Vasicek (HWV) method.

The structure of the article is as follows. In Section 2, the assumptions of the issue will include a description of the energy center model, the Monte Carlo valuation method, the energy pricing model, and the method for distributing energy. Section 3 examines the study system and in Section 4 simulation results will be shown on the system under study using Matlab software. Finally, in Section 5, the conclusions are presented.

2. RESEARCH LITERATURE

A. Energy Center

First of all, an energy center has performed the task of converting and storing several energy carriers. These centers are a new generation of power plants that have recently been of great interest and have developed in many countries [10]- [13]. A typical energy center is shown in Fig. 2. Given the growing demand for energy in the world and the high potential for electricity and heat generation at these plants, investment in the construction of these power plants is expected to increase in the future. Therefore, the purpose of this paper is analyzing the risk of investing in electricity generation and heat using energy centers. Borrowing from Bentham's [14] utility theory, Markowitz [15] was the first to adapt this concept to portfolio optimization and the institutional investment context. More precisely, he identified the fact that any rational investor (the assumption of rationality is assumed in classical and neoclassical economic theory) will require returns in proportion to the risk to which they are exposed. Alongside Slovic et al. [16] who recognized early on that the risk and return profile of an investment cannot fully be explained by referring to market risk, an increasing stream of research highlights the subjective and behavioral component of decision-making processes. Among the authors, Simon [17] argued that decision-makers opt to sacrifice rather than pursue optimal solutions. In addition to this proposition, prospect theory, as proposed by Kahneman and Tversky [18], postulated that individuals evaluate potential losses higher than potential gains. These and other behavioral economic contributions have created the foundation for further research into investor-specific perceptions about investment risk and return [19–21]. Most pre-existing risk-perception research in the energy context focuses on incumbent utilities and their reluctance to participate in the renewable energy age. Widely discussed arguments include the existence of fossil infrastructure that complicates the transformation due to its high financial and human capital investment resulting in path dependency and the slow adaptation of fixed firm structures [22,23], the overestimation of renewable energy project risk [24] and finally, the issue of which new business models may overcome the status quo [25]. Literature about the risk perception of renewable energies has mainly been designed with consumers in mind. It includes research, for example, about preferences for smart metering, service attributes or the supply contracts of utility companies, as well as the influence of eco-labels on consumer choices [26]. Research that treats consumers as renewable energy investors, has focused on their preferences for renewable energy investments, including their motivation and preferred options for financial incentives, technology, location and professional partners [27].

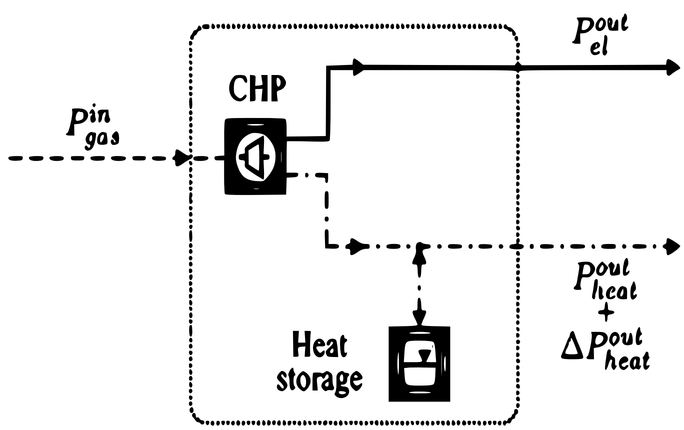

Fig. 2. Energy center with CHP unit and heat storage. The heat output can be controlled by the DSM scheme.

A few exceptions address the general risk perceptions of professional investors towards renewable energy investments [28,29]. First, pre-existing research with professional investors has mainly dealt with the interests of venture capitalists or private equity companies [28] in financially participating in clean technology, while a smaller research stream has addressed project developers [30,31]. Here, the authors argued that venture capitalists and private equity investors are early-stage investors so learning about their choices facilitates understanding of future industry booms and movements. In the meantime, renewable energy has become increasingly mainstream and institutional investors are now established market actors [32]. As a result of the experience they have gained and knowledge of their market interests, this paper investigates institutional investors in addition to incumbent utilities or venture capitalists/private equity investors. Second, previous research has investigated parts of the investment decision (e.g. policy and regulatory risks and frameworks for professional investors, diversification risk) in isolation, rather than in a natural decision framework [33].

The problem of converting and storing energy in energy centers is expressed as follows. Assuming that $P_1^{in}, P_2^{in}, ..., P_n^{in}$ inputs of different energy carriers (for example, electricity, gas, biomass, hydrogen or nuclear fuel), $P_1^{out}, P_2^{out}, ..., P_m^{out}$ the outputs of different energy carriers and c_{ij} coupling between them, The initial equation of the center can be written as (1):

$$\underbrace{\begin{pmatrix} P_1^{out} \\ P_2^{out} \\ \vdots \\ P_m^{out} \end{pmatrix}}_{P^{out}} = \underbrace{\begin{pmatrix} C_{11} & C_{12} & \cdots & C_{1n} \\ C_{21} & C_{22} & \cdots & C_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ C_{m1} & C_{m2} & \cdots & C_{mn} \end{pmatrix}}_{C} \underbrace{\begin{pmatrix} P_1^{in} \\ P_2^{in} \\ \vdots \\ P_m^{in} \end{pmatrix}}_{P^{in}} \quad (1)$$

For more detailed description of the center concept, you are referred to [34].

B. Net present value

The net present value is one of the most common methods of comparison because it has easy calculation and understanding. In this way, the discount value of all the costs or savings of a future project to the present is called the present value of that project. The discounting action is obtained from the multiplication of the desired amount at the discount multiplication, and the factor is:

$$DiscountFactor = \frac{1}{(1+r)^t} \quad (2)$$

In (2), r is the discount factor or discount rate and t is the number of years. The choice of r is based on the interest rate or bank profits. The current value of the project's savings is accumulated each year. The longer the life of the project, the more current the savings will be. Therefore, there are two main factors in calculating the current value of costs and revenues, which is a discount rate.

The discount rate in an investment plan used to calculate the present value of expected costs and revenues for the coming years is equivalent to the maximum risk-free interest rate (interest rate on long-term bank deposits or equity bonds) plus a few percents to cover the investment risk. However, the average bank interest rate in the country is 20%, and the discount rate is appropriate for calculating the plan and estimating its financial indicators with an investment risk of about 25%. This means that the costs and revenues expected for the plan over the coming years, under the name of FV^2, will be reduced by 25% annualized discount rate to PV^2, so that the problem of time value of money in calculating indicates financial considerations. In this case, the investment in a bank deposit plan with an annual interest rate of 25% is compared.

The calculation of the present value can be summarized as follows:

$$Value = \frac{S_1}{(1+r)^1} + \frac{S_2}{(1+r)^2} + \frac{S_3}{(1+r)^3} + ... \quad (3)$$

where S is the net income. The net present value by subtracting the initial construction cost of the project comes from the present value obtained in (3):

$$netpresentvalue = presentvalue - Investmentcost \quad (4)$$

In Equation (4), the ratio of the internal return of the plan is the amount of the deduction that equals zero net present value.

The net present value of the SMR power plant project is obtained in accordance with equation (5)

$$NPV = -inv + PV(CashFlows) = -inv + \sum_{i=1}^{N} \frac{CashFlow_t}{(1+r)^t} \quad (5)$$

- inv : Initial investment or initial cost
- r: Inflation in year t
- N: lifetime of the project
- Cash Flow: The turnover of the project funds in year t
- PV: is the current value of the money flow

3. MONTE CARLO EVALUATION METHOD

Monte Carlo methods are a set of computational algorithms that are based on the repetition of random numbers to compute the results with the help of event probabilities. The most important part in simulating Monte Carlo is the generation of random numbers. In general, the Monte Carlo simulation, which is based on the generation of random numbers for a random variable with multiple repetitions (1000, 2000 or more), has two basic steps.

1- Generating random numbers with uniform distribution between zero and one.
2- Converting the generated random numbers to the probability distribution function.

One of the methods for converting random numbers to the normal distribution function is shown in (6).

$$X = \mu + [-2\sigma \ln(u_1)] \times cos(2\pi u_2) \quad (6)$$

If the distribution function turns out to be useful for converting to the desired distribution, mathematical methods such as reverse conversion or reject-acceptance methods can be used. If the distribution function is discrete, then the relative cumulative function of occurrence probabilities is considered as the probability of occurrence, and the method of generating random Monte-Carlo random numbers is applied.

In general, Monte Carlo methods use techniques that apply probability distributions and random numbers to solve problems. Monte Carlo methods show a bunch of algorithms that are often used when a definitive formulation of the problem is not appropriate or the problem is not analytical and can be solved.

A common use of Monte Carlo methods is derivative pricing. For such an application, asset prices are modeled in random variables in an effective market. Although these prices show a causal relationship to the underlying economic processes, they reveal random characteristics that make them very difficult to predict.

For energy prices, this is similar. They are basically causal and depend on the balance between supply and demand, but it is very difficult to measure and analyze the various factors affecting the process of price formation. Although it may be able to predict some of the underlying price trends such as the average price change over a certain period, a precise estimate of the price of an energy carrier will rely on net luck for a year to come. Due to the lack of information about a more precise forecast, energy prices can be modeled as random variables exactly similar to prices.

One of the most suitable tools for studying random systems is simulation. Simulation is an analysis of a real world process or a system based on a mathematical model. Since a real world view is practically impossible, we must always make assumptions about the system being modeled. Simulation methods are generally effective for high complexity models that use little assumptions. Therefore, they make a realistic representation of the real world.

Monte Carlo method is used that repeatedly calculates a definite model using random sets of numbers as inputs. Such a method is often used when the model is complex and non-linear, or involves many uncertain variables. Using random entries, the definitive model necessarily changes to a random model. Many simulations are performed to calculate the model, and the law of large numbers ensures that when the number of simulations increases, the model estimation converges to the correct value [35]. The main disadvantages of Monte Carlo methods come directly from the law of large numbers: a significant amount of computational time is required for a good estimate of the "real" value.

Monte Carlo methods for complex evaluation problems with several sources of uncertainty, this method was used to evaluate energy centers. Fig. 3 illustrates the basics of this approach. The prices of all input and output energy carriers are modeled as random variables. Monte Carlo's technique involves simulating several thousand possible price paths for these energy carriers. For this reason, price modeling models such as the return average of the price logic or the Pilipovic model, which assume a two-factor representation of the behavior of the price, are assigned to the energy carriers of interest.

The energy center is modeled in the sense described in Section 2b. This concept involves the ability of an energy center to react flexibly to the volatile prices of input and / or output energy carriers and to adapt their distribution accordingly. Compared to definitive models in which only the most likely outputs are considered, the Monte Carlo method explicitly considers the operational flexibility of an energy center. To this flexibility, energy centers are able to take advantage of the rising capacity of price uncertainty, while not suffering from the same level of downside risk.

Using the random energy prices as simulation inputs, the gains derived from the energy center performance are calculated for each set of price paths. Based on these profits, the values of the energy center for each individual simulation run are computed until a certain date is reduced and averaged. In this way, the frequency distribution of the current value (PV) of an energy center is obtained.

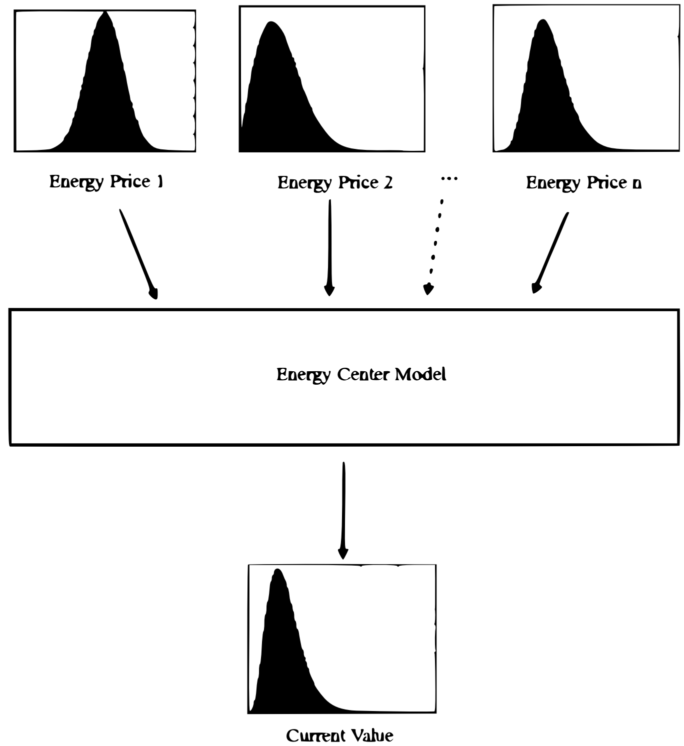

Fig. 3. The chart represents the basics of the Monte Carlo evaluation method for energy centers.

A. Modeling the price of energy

Due to the flexibility of the Monte Carlo method, in principle any costing process can be selected to model the price of energy. To illustrate the Monte Carlo Evaluation Model, the Energy Center has selected a simple price model that illustrates the main characteristics of energy price processes: The return process of the logarithm of the price . With this price model, the natural logarithm of a particular energy carrier can be expressed as follows:

$$\Delta x = \alpha \left(\mu - x\right) \Delta t + \sigma \Delta z \tag{7}$$

where x is the natural logarithm of the price of the energy carrier, the average return, μ is the average value of x in the long run, σ is the price instability and Δz is a random variable with a normal distribution with mean 1 and the variance Δt. Discrete approximation The 7th link is proposed for generating price paths for the Monte Carlo simulation.

$$x_{t+1} = x_t + \alpha(\mu - x_t)\Delta t + \sigma\epsilon\sqrt{\Delta t} \tag{8}$$

where ϵ is a random variable with normal distribution with mean 0 and variance 1.

The correlation between price paths for different energy carriers is considered by applying Cholesky decomposition to a correlation matrix. With this method of decomposition, the correlation matrix ω is decomposed.

$$\Omega = LL^T \tag{9}$$

where L is a triangular matrix. In order to create a vector ϵ_{corr} with normalized variables correlated with the correlation matrix Ω, a vector of the normalized independent variables in the first step is generated. The multiplication of this vector ϵ in the matrix L obtained by splitting the Cholesky into a vector ϵ_{corr} leads to:

$$\epsilon_{corr} = L\epsilon \tag{10}$$

where ϵ_{corr} contains a data for each energy carrier. An example of the correlated gas, electricity, and heat prices [?] is shown in Fig. 4 with the daily precision created by the above method.

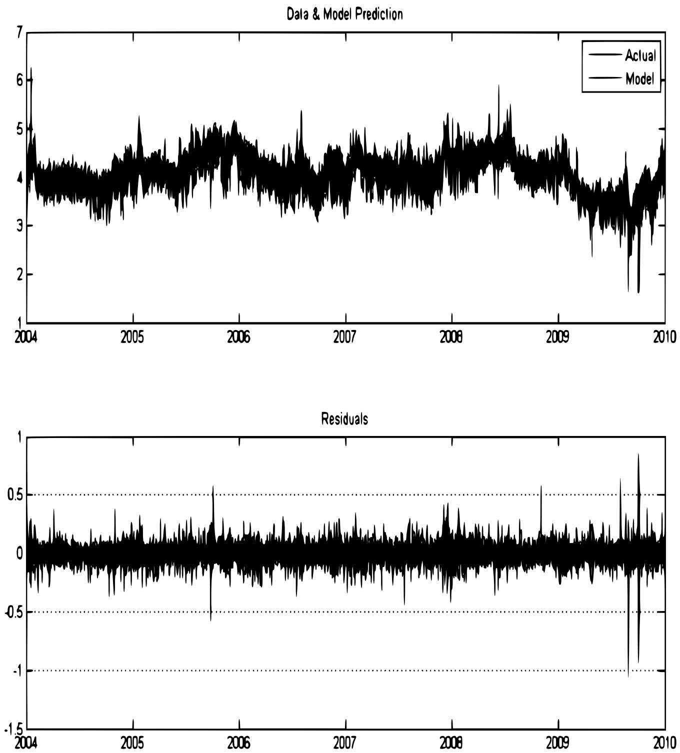

Fig. 4. The amount of predicted data for electricity pricing and its comparison with actual values and obtaining the residual value.

For the assessment of energy centers, the assumption of a precision of the daily price, that is, only one price every day, is not enough. The number of stepping-ups in one day will increase, the more reliable the results will be. The average return value model is the price of a particular case of the HWV model with changes in volatility. Using this model, the average value and average return rate are obtained and then, using the Monte Carlo method, the prices of future years are obtained.

In the HWV model, there are two general parts: 1) random and 2) predicted parts. The predicted part is obtained using the data of previous days, the day of week and hour, and the random part is modeled as seasonal fluctuations. The price of power failure is directly related to the price of the fuel input, the season, the day of the week and the hour of the day.

Using the HWV relationships, the predicted part of the available data is obtained. Then, in order to model the random part, its residual value is obtained from real values.

Residual values may also have some serial dependencies. This thread is simulated by the ACF function.

In this simulation, the relation between x_t and x_{t+k} is obtained so that $K, ..., k = 0$ are random processes. The latency of r_k is as follows:

$$r_k = \frac{c_k}{c_0} \tag{11}$$

where in

$$c_k = \frac{1}{T-1} \sum_{t=1}^{T-k} (y_t - \bar{y})(y_{t+k} - \bar{y}) \tag{12}$$

And C_k is the sample variance of time series.

The estimated standard deviation for correlations in k interval is expressed as follows.

$$SE(r_k) = \sqrt{\frac{1}{T}\left(1 + 2\sum_{j=1}^{q} r_j^2\right)} \tag{13}$$

where q is the delay in which ACF is zero.

If the series is selected randomly, the standard deviation will drop to $\frac{1}{\sqrt{T}}$.

The model applicable to the random can be the SDE recursive average model. However, due to the seasonal nature of random data, the auto-regressive model is used with seasonal delays. Therefore, delays between 1-4 hours and 1-2 days are used.

Because the residual values are not large enough, they can be selected by an appropriate distribution function. Residues should be modeled by distributing the fatter tail instead of Student-T. So Pareto's distribution is used for modeling. Fig. 5 shows how to compare the remaining available data and distribution functions. As it's clear from this form, the Pareto distribution function has a better overlap than other functions.

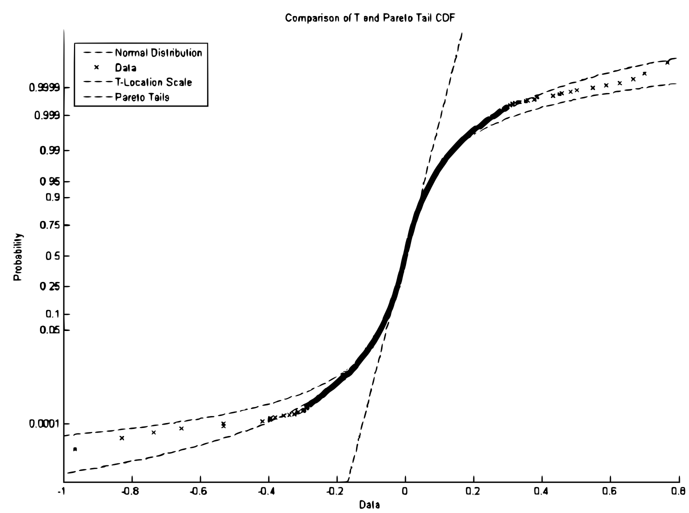

Fig. 5. Compare distribution of Pareto with Student-T

Finally, the simulated model and the available values for 2009 are compared with each other that have a very good overlap.

B. Optimal distribution and evaluation of the energy center

The basis for calculating the value of an energy center is the calculation of daily profits from performance. Depending on the timing of the simulation of the energy price, the time interval is divided into N_t, depending on the time horizon of the analysis. With this definition, daily profits F_d can be calculated for each set of simulated price paths for input and output energy carriers.

$$\mathrm{F_d} = \sum_{t=1}^{N_t} \left(\left(P_t^{out}.\pi_t^{out} \right) - \left(P_t^{in}.\pi_t^{in} \right) \right) \tag{14}$$

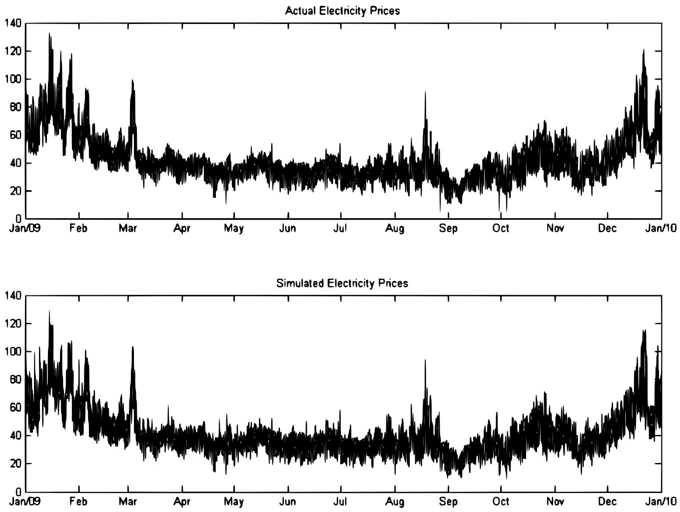

Fig. 6. Compare Simulated and Available Data for 2009

where P_t^{out} and P_t^{in} are output and input power vectors at each instant t, and $_t^{out}$ and $_t^{in}$ the corresponding prices are input and output energy carriers.

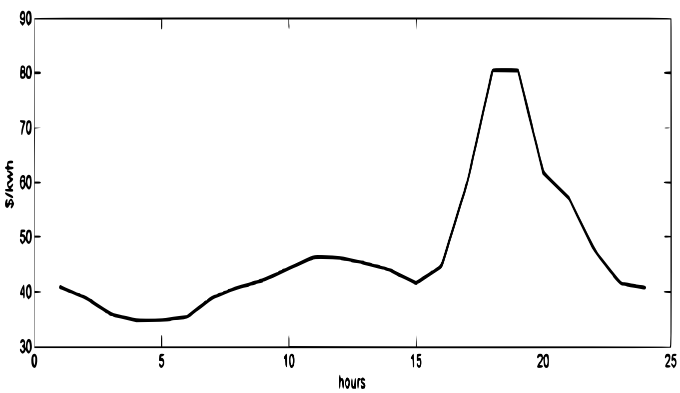

Fig. 7. Sample the price of heat $(\Delta t = 24h)$

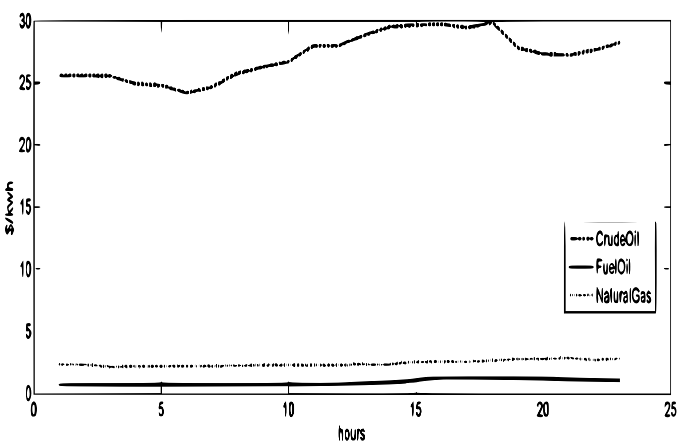

Fig. 8. Sample input fuel prices of heat $(\Delta t = 24h)$

This means the daily profits of F_d are obtained in the form of a difference between the proceeds from the sale of energy carriers and the costs incurred in purchasing energy inputs. Input and

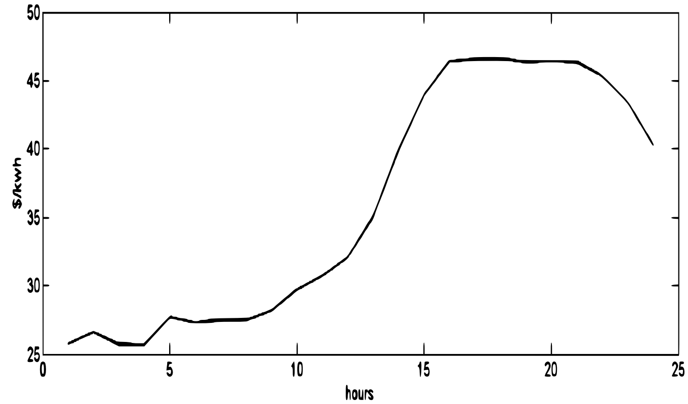

Fig. 9. Sample prices of heat $(\Delta t = 24h)$

output power are determined by optimizing the distribution of energy at the energy center. In the energy center model presented in this paper, optimal performance means maximizing daily profits. Simulated energy prices are used as inputs for optimization. For each set of simulated energy prices, that is, for each simulation day, the following optimization problem is solved:

The goal is to minimize the following function.

$$f\left(P_t^{in}.v_t.H_t\right) = \sum_{t=1}^{N_t}\left(\left(P_t^{out}.\pi_t^{out}\right) - \left(P_t^{in}.\pi_t^{in}\right)\right) \quad \textbf{(15)}$$

The terms of the problem are expressed as follows.

$$P_t^{out} - CP_t^{in} - DH_t = 0 \quad \textbf{(16)}$$

And

$$P_{min}^{out} \leq P_t^{out} \leq P_{max}^{out} \quad \textbf{(17)}$$

$$H_{min} \leq H_t \leq H_{max}$$
$$0 \leq \mathrm{v_t} \leq 1 \quad \textbf{(18)}$$

The objective function is optimized by changing the input power P_t^{in}, the distribution coefficient v_t, depending on the price of $_t^{out}$ and $_t^{in}$. Equation (15) ensures that input power is converted only to the electrical and thermal energy of the output. Equation (16) to Equation (18) ensures that the limits of minimum and maximum power are maintained. At each simulation time, the value of the objective function $f(P_t^{in}.v_t.H_t)$ is used to calculate daily profits $F_d according to Equation 14. When daily profits are determined through an optima$
F_d daily profits are directly equal to the daily returns of B_d.

In this paper, it is assumed that the minimum profit is zero (the energy center is not used). So, daily returns are as follows:

$$\mathrm{B_d} = \max\left[\mathrm{F_d};0\right] \quad \textbf{(19)}$$

$$\mathrm{B_{run}} = \sum_{t=0}^{T}\left(B_{d.t}.e^{-rt}\right) \quad \textbf{(20)}$$

where r is the adjusted interest rate with continuous risk. Continuous interest is used because it is an appropriate approximation for real daily interest. In addition, the modifications of the model, such as taking into account variable time rates, make it easy. Finally, the value of the energy center is obtained by averaging the payments of all N simulations.

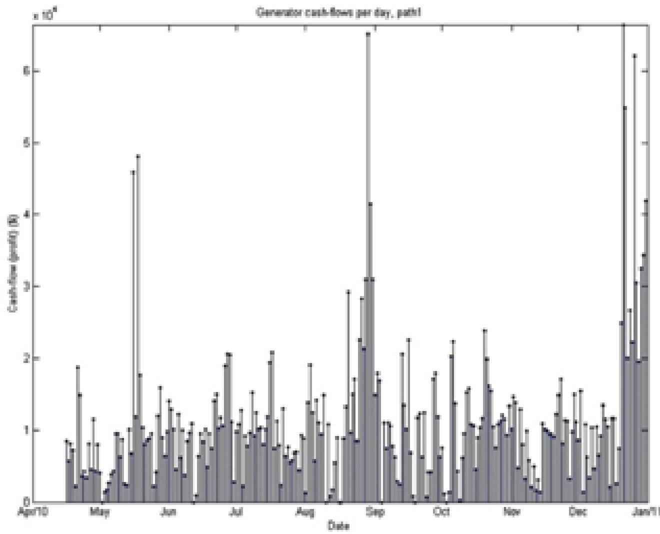

Fig. 10. Daily Profits of the Energy Center

$$V = \sum_{n=1}^{N} \mathrm{B}_{\mathrm{run.n}} \cdot \frac{1}{N} \tag{21}$$

Then, the value of the V energy center can be compared to the initial investment cost I of it. If $V > I$, the investment is profitable with the assumptions made in the modeling process. If $V < I$, the investment cost is greater than the value of the energy center, and the investment in this configuration of the energy center is ignored.

4. SYSTEM ANALYSIS

The following application example shows the proposed investment evaluation method for energy centers that can respond with flexibility to uncertain energy prices.

The price of incoming fuel, heat and power carriers from 2008 to 2014 is Henry Hub. By using Equation 7, these prices will be achieved for 2015-2017. The graph shown in Fig. 11 shows an example of the price of energy carriers in the years 2008 to 2014. These projections include the effects of the weekend or season chapters.

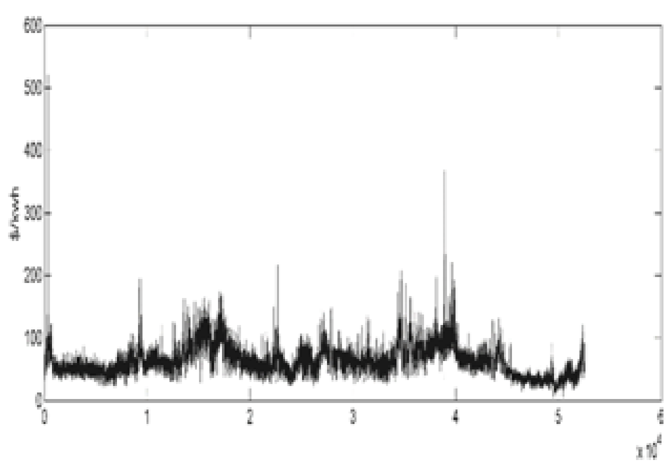

Fig. 11. Electricity prices from 2008 to 2014

Table 1. Energy Center Parameters

Heat and heat generation unit	
Electrical efficiency	$\eta_{chp,el} = 0.33$
Thermal efficiency	$\eta_{chp,heat} = 0.57$
Named electrical capacity	$P_{max}^{out,chp,el} = 100MW$
Initial investment cost	$3\frac{\$}{MWh}$
Minimum operating time of the center	12 hours

The parameters of the CHP unit and the hot water reservoir are listed in Table 1.

The total area heat consumption is about 250 GWh per year. Figure 10 shows the associated thermal load curve with its seasonal variation for 8760 hours per year.

With the proposed method in this paper, using different prices, load traffic is achieved for each scenario or path obtained. Ultimately, profitability and risk are obtained at 95% and 90%. The waveform shown in Figure 11 shows this risk. This configuration would result in an expected $3 million expected average of$ 1 million in standard deviation, or 33% in the medium.

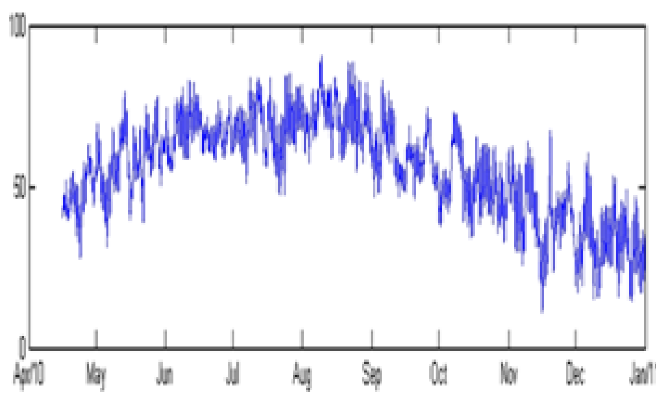

Fig. 12. Thermal load curve for one year

5. CONCLUSION

In this paper, the risk of investing in energy centers was studied. Due to the uncertainty in input parameters, NPV calculations were performed in uncertainty mode using the Monte Carlo method and HWV method. By analyzing the numbers obtained in two cases, the appropriate investment risk and the economics of the project for constructing the energy center are discussed. Based on the results of the paper it is clearly assumed that investment risk analysis could be mentioned as an important parameter to plan a power system energy center which is combined of multiple energy resources as it affects the profit of the energy center. Therefore, it would be such a helpful study if somebody focused on statistical data of a real energy center to obtain an applicable result of this paper, in the future researches.

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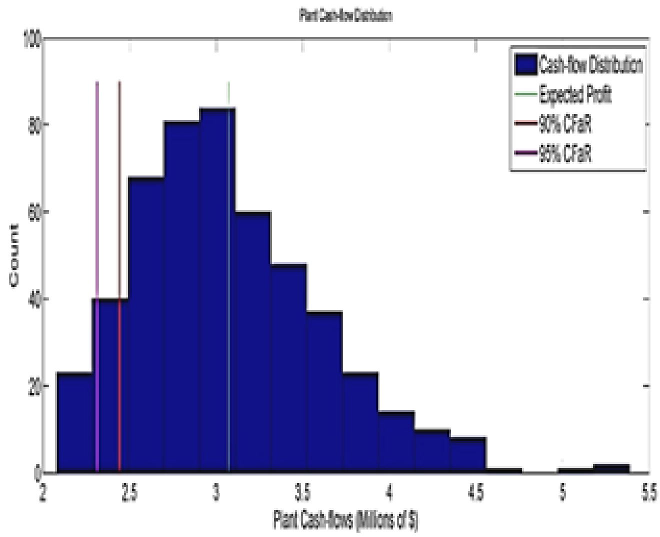

Fig. 13. Investment risk, 90% risk and 95% profitability

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