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Energy economy in regulated and market-based power system: case study in Serbia

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Abstract: This study presents a possible process of simulating power plant generation planning. The process combines expected overall industry costs, associated cost uncertainty, and expected CO_2 emissions for different generations, variations of future fossil fuel costs, carbon prices, plant investment costs, and demand, including price elasticity impacts. Uncertainty in the decision stems from the elasticity of prices of fuel and electricity. The aim of this paper is to apply fuzzy numbers to power generation planning and to use a Monte Carlo simulation to check. Simulations are demonstrated through a case study of an electricity industry with coal and lignite, combined cycle gas turbines, and supercritical boilers facing future uncertainties. The same simulation was used in planning the generation of electricity from wind, solar, and hydro energy. Comparing the results, decisions were made about the profitability of investments in renewable energy. Based on the results, it can be concluded that the use of fuzzy numbers is a simple and flexible approach to planning and that it can be a serious competitor compared to other methods of planning.

Key words: Generation planning, renewable energy, price elasticity, Monte Carlo, fuzzy logic

1. Introduction

An adequate supply of electricity is a prerequisite for the economic development and social well-being of a country. For every country, energy and environmental issues are very complex. These issues generally involve many sources of uncertainty, long time frames, and a large number of variables. For these reasons, the application of decision analysis methods is very suitable for these issues [1]. Generation investment represents, among others, the most critical and challenging decisions undertaken within an electricity industry [2]. Investments are important for generation planning but also necessarily undertaken in the context of projections of future electricity demand. An analysis of long-term planning generation plants has shown that differences in the expected and real results always exist. That difference is present whenever uncertainties of a decision exist. Expanding the time period of a project leads to a larger uncertainty of plans. Investments in the power sector are enormous and always require a relatively long-term planning horizon. Fundamental risks for planners in power systems in making resource decisions include technological changes, fuel costs, load growth, economic trends, and environmental concerns [3]. The aim of the market participant is to align the plan of the project in a market environment with the smallest risk. That kind of problem requires a high level of complexity and uncertainty of an evaluation. Many papers solve this problem by applying decision analysis methods. The method is divided into 3 major groups of methods that deal with a similar problem as this paper: single objective decision making methods [2,4,5], multicriteria decision-making methods [6–11], and decision support

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systems [12]. Other decision-making tools used in renewable energy (RE) investment projects are fuzzy sets and systems, and they cannot be classified as any of the above 3 methods. Those methods are used to evaluate solar system and wind site selection [13–15] and in geospatial multicriteria analysis methodology to deploy wave energy farms [16], and are used to make decisions on planning distributed generation and its influence on the power system [17–23]. Variations of these methods are applied in the form of 'if' rules, whereby the behavior of criterion functions are observed. In such methods fuzzy expert systems are often used, but rarely fuzzy numbers. In variations of variables in project planning, MCS is also often used [24–26].

Except hydro, Serbia has limited experience with RE. Furthermore, there is a lack of studies comparing existing thermal power plants to electrical power plants utilizing renewable resources. However, this drawback could turn into an advantage, because now we can also include the market effects. Serbia is following the path to join the European Union as a member state and incorporates EU legislature, including legislature related to electrical power markets (e.g., the open access rule). In this paper we applied 2 methods to assess the economic risks of investing in RE sources. Difficult questions for economic decision-makers include variations in consumer demand, increase or decrease of prices or interest rates, and many other uncertainties. Answering these questions is not easy, because the future is not fully predictable, especially in Serbia. For this reason, in this paper we apply 2 methods (Monte Carlo simulation [MCS] and fuzzy numbers) to assess the economic risks of investing in RE sources. This paper presents the portfolios of investment and discusses how to plan investments and production capacity in the regulated electricity system and market environment to mitigate risk. The price of electricity varies through both methods depending on the load. The paper defines blocks of work of power plants that are correlated with the pricing tariffs. The simulations involve economic parameters for 5 different technologies with conventional and RE sources, fuel prices, and electricity and CO_2 taxes.

2. Basic concepts of power plant generation planning

Methods of assessing and ranking investment projects consist of a set of procedures by which the system learns about the acceptability or unacceptability of investing. The purpose of economic analysis is to determine the feasibility of a certain project with respect to the global economy of the country. The electric power industry and power producers need to decide on certain types of power plant projects. Investment realization options typically differ regarding the dynamics of expenditures and revenue and cannot be directly compared. For this reason, special methods have been developed to compare investments, which convert all cash flows associated with a project to the equivalent values related to a specific moment in time, using a particular update rate. In this paper, the method of the present worth (PW) was used. PW is one of the methods of equivalent value and consists of reducing all cash flows of a project in the present moment, using the following formula:

$$PW = -C_I + \frac{R_1}{(1+i)^1} + ... + \frac{R_n}{(1+i)^n} + \frac{C_{res}}{(1+i)^n}. \tag{1}$$

In Eq. (1), C_I is the present value of capital investment in the investment project, R_t is annual net cash flow (the difference between annual income and expenses), i is update rate, C_{res} is the residual value of the investment project, and n is the life of the investment project. A project is cost-effective and acceptable if:

$$PW > 0. \tag{2}$$

Fuel (c_F [€/GJ]), electricity (c_e [€/MWh]), and other prices entered in the budget are not fixed in the long term. These prices must be varied to see what would happen to the profitability of the project. System load and electricity demand are not always the same and are shaped by the load duration curve (LDC). The LDC is correlated with c_e. The connection between the load and the prices of electricity has to be defined and taken into account. It is necessary to detect the period of time when the production of selected plants does not make a profit. Such periods of plant operation have been removed from the calculations. Input data and formulas in these methods are as follows:

$$MC = VC_{O \wedge M} + HR \cdot c_F + EF_{CO2} \cdot c_{CO2}, \tag{3}$$

$$EC = CF \cdot 8760h \cdot P_{\max} \cdot 10^{-6} \cdot MC + FC_{O \wedge M}, \tag{4}$$

$$I = CF \cdot 8760h \cdot P_{\max} \cdot 10^{-6} \cdot c_e, \tag{5}$$

$$P = I - EC, \tag{6}$$

$$PVF = \frac{1}{(1+i)^n}, \tag{7}$$

$$PWF = \frac{(1+i)^n - 1}{(1+i)^n \cdot i}, \tag{8}$$

$$PW = -IC + P \cdot PWF + RV \cdot PVF. \tag{9}$$

In Eq. (3), MC [€/MWh] is marginal costs, $VC_{O\&M}$ [€/MWh] is the variable cost of operation, HR [GJ/MWh] is the heat rate of power plant, EF_{CO_2} [tCO_2/MWh] is the CO_2 emission factor, and c_{CO2} [€/tCO_2] is price of CO_2 emissions. In Eq. (4), EC [million €/year] is the exploitation of the generation plant, $P_{\max}$ [MW] is the maximum capacity of the power plant, CF is the capacity factor, and $FC_{O\&M}$ [€/year] is the fixed cost of operation and maintenance. In Eq. (6), I [million €/year] is the income earnings of plant and P [million €/year] is the profit of plant per year. In Eqs. (7) and (8), PVF is the present value factor and PWF is the present worth factor. In Eq. (9), IC [million €] is the investment capital cost and RV [million €] is the value of the plant after n years. Using Eq. (9) for any combination of inputs, for the selected power plant, we get the PW. The advantage of RE sources is that c_F and EF_{CO2} are zero [6]. That is applied to Eq. (3).

3. Monte Carlo simulation

MCS can be defined as a statistical simulation method, and we use sequences of random numbers for the execution of the simulation. In recent decades, MCS has received a fully completed status and it is one of the numerical methods capable of solving the most complex conditions requirements [27]. MCS was originally known as 'statistical simplification'. It is capable of addressing many of the limitations of decision analysis and of sensitivity analysis [28].

The final profile of the project depends on the different scenarios regarding movement of essential inputs. The analysis conducted for this example will have possible deviations (c_F and c_e) in the market in the range of 85%–115% of the expected values considered in the baseline scenario. The components will be modeled on uniform distribution in the range set boundaries; it is accepted that there will be other model parameters from the expected values. MCS was applied as a tool to determine probability distributions for economic indicators. MCS allows sampling techniques to simulate the effects of fluctuations in economic parameters, and because of that it is suitable for risk assessment [29]. MCS was performed with the probability distribution of the value of the project based on PW, simultaneously incorporating the probability distribution of essential inputs. The advantage of this concept is that it can be easily visualized, understood, and interpreted, which is important for policy makers, because they can see the project profile on the basis of only one or a few graphs. Graphic presentation can be done in many ways, and this will be displayed when using the value at risk (VAR) histograms and curves [30]. The histogram shows the probability that PW will fall in the range of values ??indicated by the median value of the intervals. The VAR curve illustrates the cumulative probability distribution and can be considered more informative than a histogram. The curve provides information about the probability that the project will earn at least X units of currency (€) and the probability that it will generate a loss.

The market price of electricity has a significant impact on the position of a power plant in the market. Each year of the studied period was used for block pricing for modeling c_e in the market. These pricing blocks are correlated with the consumption of blocks, which can be approximated by a LDC. Some methods '?t' the available generation options to a speci?c LDC to determine the mix of technologies and their respective capacity factors that minimize industry costs. In this paper, we want to make a global decision about which type of power plant has the best profit based on LDCs. The market price of electricity is divided into 3 parts: an upper block, middle block, and basic block. 'Basic block' refers to periods of time when the demand for energy is small, so the price for this block (c_{Be}) is lower than that of the middle block and has a value of 65.57% of c_e. It is accepted that this block accounts for 40% of the time (3504 h/year), while the middle block occupies as much as the upper block, or 30% of the time (2628 h/year). The price for the middle block (c_{Me}) is 100% of the average price, while the peak block price (c_{Pe}) is 150%, because then there is also the greatest demand for electricity. The described process of reasoning is presented in Figure 1. The observed power is only in the moments when the electricity price in the market is higher than the marginal cost. That is the only time it makes sense to produce electricity and create potential profits. This fact is taken into account by applying the formula

$$c_e = k_p \cdot c_{Pe} \cdot 0.3 + k_M \cdot c_{Me} \cdot 0.3 + k_B \cdot c_{Be} \cdot 0.4 \tag{10}$$

to Eq. (6). In Eq. (10) k_P, k_M, and k_B are logical coefficients that take the values ??0 and 1 according to the described procedure probation. In this way, we have taken into account the work of the power plant for the exploitation period.

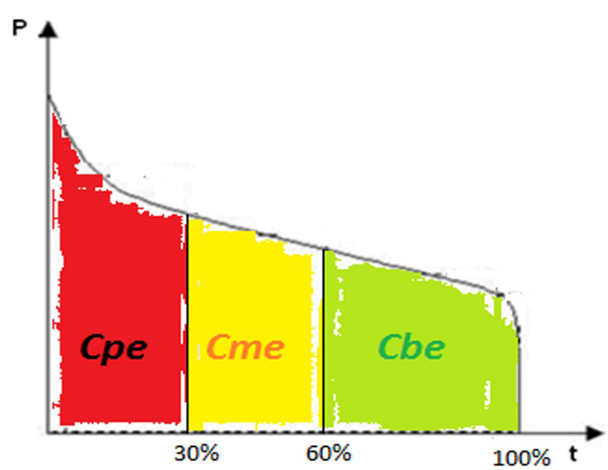

Figure 1. LDC with 3 pricing blocks.

4. Fuzzy logic

Risk analysis is performed in the interpretation of large quantities of information to make a proper decision [31]. New mathematics considers 'inaccuracy' and 'fuzziness' in a logical manner [32]. One such method is based on fuzzy logic, which interprets input variables as fuzzy numbers. Fuzzy logic is a mathematically formalized model that can show uncertainties. In classical clear set theory, any particular element (x) either belongs or does not belong to a defined set. In other words, the belonging of elements is extremely distinctive. Fuzzy entities are sets with nonsharp boundaries in which there is a transition between elements that belong and elements that do not belong to the set. Fuzzy set (A) is, in this sense, a generalization of classical set (X), since the membership (i.e. membership level) of the element to the fuzzy set can be characterized as a number from the interval [0,1]. In other words, the membership function $(\mu_A(x))$ of the fuzzy set maps each element of the universal set of the mentioned interval of real numbers:

$$A = [x, \mu_A(x) | x \in X] \tag{11}$$

In recent years, fuzzy optimization, and especially fuzzy linear programing, is utilized in many economic areas, such as energy planning. In this paper we worked with c_e and c_F as the 2 variables, which are presented as fuzzy numbers. As such, they are entered into the budget and used in Eqs. (4) through (10). The result is PW in the form of a fuzzy number. Results of MCS are verified on the basis of such a result. The first step in the implementation of fuzzy numbers is fuzzification. Fuzzification simply modifies the input signals so that they can be properly interpreted. This is provided by the membership functions, which map the degree of truth claims. Membership functions are a continuous measure of safety. The membership functions for c_e and c_F are shown in Figure 2. The biggest probability, $\mu(c)= 1$, is that the price takes the exact 100% value prices. The other probabilities are that the price deviates between 85% and 115% of the minimum. Thus, selected membership functions correspond to inputs in MCS.

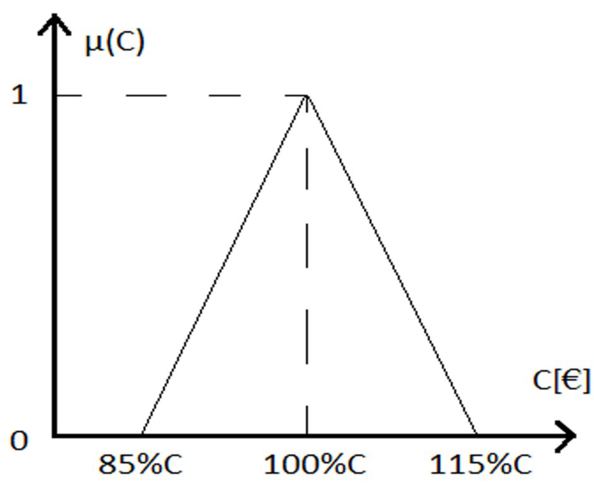

Figure 2. The membership functions for c_e and c_F.

During the implementation of the operations of addition, subtraction, multiplication, and division of fuzzy numbers, membership functions can be expressed as follows:

$$\mu_C(z) = \mu_{A+(-,*,/)B} = \max\{\min[\mu_A(x), \mu_B(y)]\}. \tag{12}$$

If $A(a_1, a_2, a_3)$ and $B(b_1, b_2, b_3)$ are fuzzy numbers with their intervals that determine the α-level of belonging, then the basic arithmetic operations are defined as shown below.

$$\begin{aligned} A+B &= (a_1+b_1, a_2+b_2, a_3+b_3) \\ A-B &= (a_1-b_1, a_2-b_2, a_3-b_3) \\ A\cdot B &= (a_1\cdot b_1, a_2\cdot b_2, a_3\cdot b_3) \\ A/B &= (a_1/b_3, a_2/b_2, a_3/b_1) \end{aligned} \tag{13}$$

The result, PW, is in the form of a fuzzy number, whose membership functions are triangular in shape. It is necessary to transform this result to a number. Defuzzification, which is the final step in fuzzy logic, transforms the interface conclusion into a signal representing the output. The output must have a unique value, usually represented by a real number. Methods commonly used for defuzzification are: center of the surface (gravity), the sum center, the center of the largest surfaces, first maximum, middle maximum, and height defuzzification. The method applied was the center of gravity:

$$PW = defuzzy(\mu(PW)) = \frac{\int \mu(PW)\cdot PW \cdot dPW}{\int \mu(PW)\cdot dPW}. \tag{14}$$

As a final result of application, it is possible to produce a single fuzzy number, despite numerous PW values ??and their probabilities. For the selected value of the PW on the axis, it is possible to determine the value of the membership function probability, from the following formula:

$$\mu(PW) = \left\{ \begin{array}{c} 0, PW \le PW_L \\ \frac{PW-PW_L}{PW_{100}-PW_L}, PW_L \le PW \le PW_{100} \\ -\frac{PW-PW_B}{PW_B-PW_{100}}, PW_{100} \le PW \le PW_B \\ 0, PW \ge PW_B \end{array} \right\}. \tag{15}$$

In Eq. (15), PW_L is the worst/lowest value and PW_B is the best/highest value of PW. This result gives us a picture of possible PWs. Based on all of this, a decision about investing power can be made.

5. Case study and results

The case study involved conventional energy, an electricity industry with conventional pulverized coal, a combined cycle gas turbine (CCGT), and lignite with supercritical boilers (ST). Electricity industries with RE sources were wind (WG), solar (SG), and hydro (HG) energy generation. Every generation option has uncertain future fuel prices, carbon prices, demand, and capital costs. They also possess different characteristics in terms of capital costs, fuel, operating costs, and carbon emissions. The case study imitated a 25-year plan ($n = 25$) with an interest rate of 9% ($i = 9\%$). Technical parameters and characteristics of each technology used in this study are taken from [33,34] and are presented in Table 1.

MATLAB technical computing software was used to apply MCS and fuzzy numbers [35]. For each of the 5 generations, MCS determined a probability distribution of PW. The total number of simulations (simulated future fuel prices, fuel price, demand, and capital costs) was 10,000. These simulations provided results about uncertain costs to compare to the expected costs. MCS results are shown in Figures 3 and 4. Information for the possible values of PW for ST, CCGT, and WG are displayed using a histogram (Figure 3). Figure 4 is a comparative VAR curve. It was found that investments in ST carried a risk of –8.3% of the project value and therefore was less risky than an investment in CCGT, which had the probability of –28.7% of the project value. For renewable resources, there was no negative risk. From the histogram, it can be seen that WG had the highest risk and HG had the least risk. The assigned membership functions for c_e and c_F are shown in Figures

5 and 6. Electricity prices for RE power plants were taken in accordance with the feed-in tariff for Serbia. After performing calculations with those prices, the results obtained in the form of PW fuzzy numbers were as shown in Figure 7. Based on Figure 7, we can see that the PW for power plants was of the same order as in the MCS. Based on both methods, in this study, the conclusion is that it is more cost-effective and less risky to invest in building HG resources.

Table 1. Technological parameters.

Technology	ST	CCGT	WG	HG	SG
n [years]	25	25	25	25	25
IC [million €]	450	210	393	306.3	544.5
RV [million €]	45	21	39.3	30.63	54.45
$P_{\max}$[MW]	270	288	280	280	280
CF [%]	84	89.2	31.1	44	15
EF_{CO2}[tCO_2/MWH]	0.9	0.33	0	0	0
HR [GJ/MWh]	9.8324	6.52704	0	0	0
$VC_{O\&M}$[€/MWh]	1.7	1.3	2.666	2.65	0
$FC_{O\&M}$[€/year]	12.5×10^6	4×10^6	2.7×10^6	2.95×10^6	21.4×10^6
C_F [€/GJ]	1.5	7.5	0	0	0
C_e [€/MWh]	60	60	95	78.5	230
C_{CO2} [€/tCO_2]	6.8	6.8	0	0	0

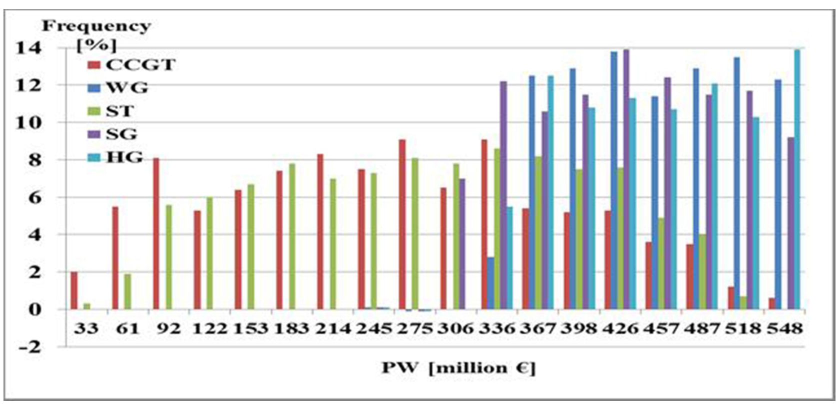

Figure 3. Comparative histogram of PW for different types of generations.

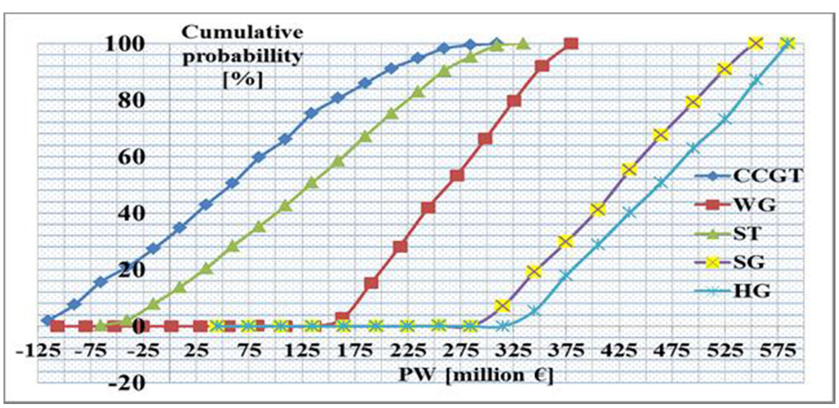

Figure 4. Comparative VAR curves of PW for different types of generations.

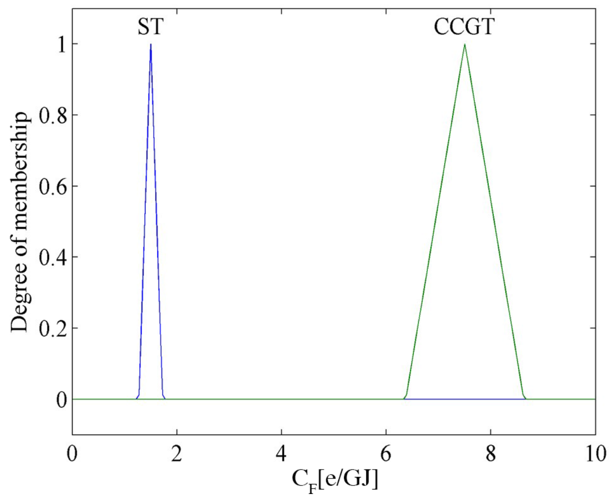

Figure 5. Membership functions for c_F.

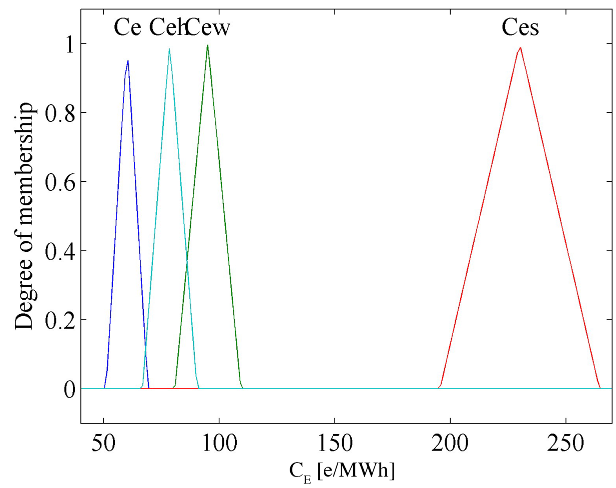

Figure 6. Membership functions for c_e.

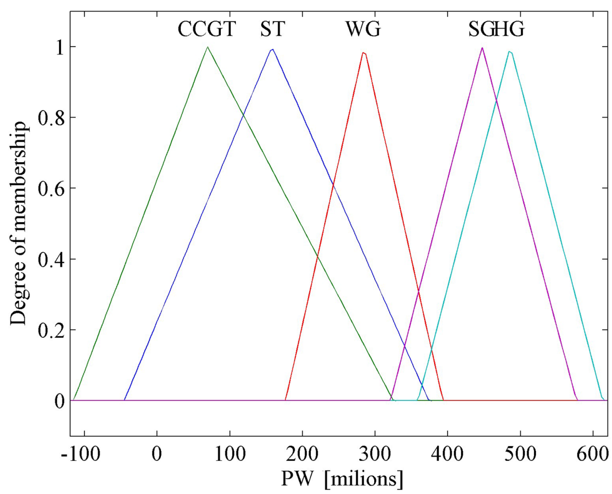

Figure 7. Membership functions for output PW.

Each fuzzy number is characterized by 3 values that represent the minimum, probable, and maximum value for PW. Comparative values of MCS were made using the formulas shown below.

$$\begin{aligned} PW_{\min} &= \min(\sum_{i=1}^{10000} PW_i) \\ PW_{\max} &= \max(\sum_{i=1}^{10000} PW_i) \\ PW_{mean} &= (\sum_{i=1}^{10000} PW_i)/10000 \end{aligned} \tag{16}$$

These 3 values of MCS and the defuzzification value of PW were compared. The results and mutual deviations are presented in Table 2. Discrepancies in the results of the applied methods exist, but they are small and can be ignored because the final decisions were the same. The use of MCS and fuzzy logic is justified and leads to the same conclusions.

Table 2. Comparison of the results.

Technology		ST	CCGT		WG	HG	SG
Method	PW [10^6 €]						
MC S	PW_{MIN}–61.54–123.8	170	311.2	347.61			
MCS	PW_{MEAN}	141.66	72.22		275.13	438.35	475.25
MCS	PW_{MAX}	345.50	309.29		383.95	560.44	596.95
FL	PW_{MIN}–45.7–115.4	176.8	359.42	321.05			
FL	PW_{MEAN}	157.8	69		284.75	486.29	447.48
FL	PW_{MAX}	373.7	324.9		392.7	613.15	577.57
FL	$PW_{DEFUZZY}$	161.93	92.83		284.75	486.29	448.7
$\varepsilon(PW_{MIN})$ [%]		26.87	6		3.53	15.5	7.6
$\varepsilon(PW_{MEAN})$ [%]		11.9	4.45		3.49	10.9	5.84
$\varepsilon(PW_{MAX})$ [%]		7	5.1		2.27	9.4	3.2

6. Conclusions

This study presents a novel and comprehensive generation investment decision-making method aimed at helping future electricity generation mix assessment under uncertainty. The uncertainty comprises future fuel prices, carbon emission prices, plant investment costs, and electricity demand, including price elasticity impacts. The presented method and the results confirm the validity of applying fuzzy logic in making appropriate decisions about investment planning. The results justify the use of fuzzy numbers for planning electricity production. The results presented in the form of fuzzy numbers give a broader view of possible developments in planning projects. Unlike existing decision analysis methods, this method of using fuzzy numbers is quite simple and requires only basic input data for different types of generating electric energy. The applied methods and numerical experiments accounted for the volatile postwar situation in Serbia and the region. The benefit in selecting the time scale for the benefit/cost analysis is that hardly any investments in the energy sector were made for more than 2 decades in Serbia. Energy consumption, especially electrical energy consumption, has shifted from industrial to residential and commercial loads without any large investments in power plants and almost negligible investment in RE sources. This study is important for stimulating investment in Serbia in electricity production from RE and provides insight into economic profitability.

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