**Radosław Winiczenko**

ORCID: 0000-0001-6566-5933

Warsaw University of Life Sciences
Faculty of Engineering Production
Institute of Mechanical Engineering
ul. Nowoursynowska 164, 02-787 Warszawa, Poland

radoslaw_winiczenko@sggw.edu.pl

# Application of the genetic algorithm to the estimation of energy consumption in Poland

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**Abstract.** This work aims to model and estimate electricity consumption in Poland using a genetic algorithm approach. The genetic model was based on socio-economic data such as GDP, imports and exports, and population growth. The data covered the period from 1990 to 2024. Quadratic and exponential models were tested in this study. The exponential model was demonstrated to be the best fit to the data. The best mean absolute error was obtained for the exponential model, MAE = 0.0276, for a population size of 100, a crossover probability of 0.85, and a mutation probability of 0.02. The projection of electricity consumption in Poland was also demonstrated and compared with the data from the literature. The genetic model forecasts an electricity consumption of 211 TWh in 2040.

**Keywords:** Energy consumption, Genetic algorithms, Modelling, Future projection

# 1 Introduction

In Poland, electricity is produced primarily by utility power plants. According to data from [1, 2], electricity production in Poland in 2024 amounted to 167 TWh. It was an increase of 2.05 % more than in 2023. Domestic consumption was 0.86 % higher year-on-year and amounted to 167 TWh (Figure 1).

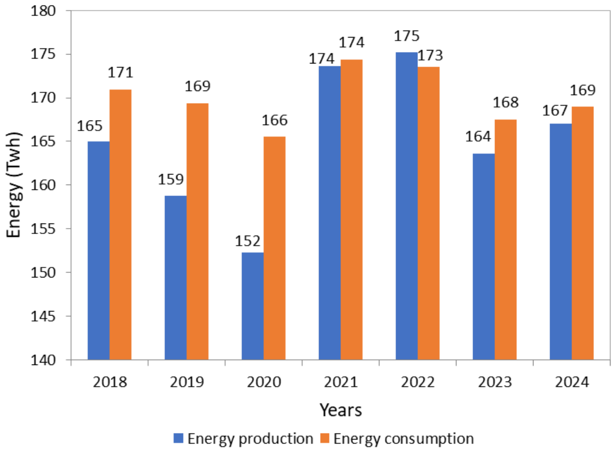


**Figure 1.** Electricity production and consumption in 2018-2024 (TWh). Source: own elaboration in Excel on the basis [1, 2].

As shown in Figure 1, electricity production in 2024 was lower than domestic consumption. Consequently, the foreign exchange balance was positive and amounted to 1.97 TWh. In 2024, these facilities produced 124.78 TWh, representing almost 75 % of total production. The remainder was accounted for by wind farms and other renewable energy sources (approximately 42.21 TWh). The most important fuels used for electricity generation were hard coal, with a 41.4 % share, and lignite, with a 21.5 % share. Renewable energy sources produced 42.22 TWh, increasing to 25.3 %. After 2020, the primary increase is in electricity consumption, driven by economic growth and the electrification of transport. Renewable energy sources also grow, increasing the consumption of solid biomass, ground energy, and solar energy (solar collectors, heat pumps, geothermal sources). The decline in biofuel use after 2025 is due to the popularisation of electromobility [3, 4].

The structure of electricity production in Poland in 2024 is shown in Figure 2.

Total electricity production increased by 2.05 % year-on-year to 167 TWh in 2024 [1, 2]. The production from coal (hard coal and lignite) accounted for 63 % of the total last year. In contrast, production from renewable energy sources (i.e., hydro, wind, and other renewable energy sources) accounted for 27 % (Fig. 2). Throughout 2024, commercial thermal power plants produced 69.11 TWh of electricity from coal (a 9.78 % decrease year-on-year), 35.84 TWh from lignite (a 3.68% increase year-on-year), and 16.77 TWh in gas-fired power plants

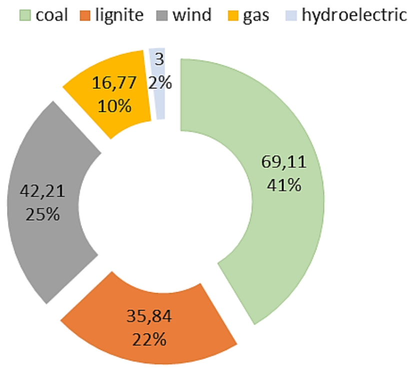


**Figure 2.** Structure of electricity production in 2024. Own elaboration in Excel on the base data [20].

(a 22.84 % increase). Wind power plants produced 24.87 TWh of energy (a 13.07% increase year-on-year), hydropower plants produced 3.06 TWh (a 14.89 % decrease year-on-year), and other renewable energy sources produced 17.33 TWh (a 31.23 % increase). It is worth noting that in 2024, the share of coal decreased to 56.2% and the share of renewable energy increased to 29.4 %. Wind energy was the dominant renewable energy source (14.5 %), while production from natural gas also increased significantly (12.2%), reaching a record level [3, 4].

## 2 Literature review

Recently, many work has been devoted to estimating electricity consumption using artificial intelligence methods [5–12]. The authors conducted a study on forecasting electricity consumption for Pakistan. Electricity estimation using a genetic algorithm in Turkey was achieved in papers [5]. The authors linked energy consumption to economic factors such as gross domestic product growth (GDP), imports, exports, and population size in these papers. These relationships were characterized by significant nonlinearity over time. Therefore, various forms of mathematical functions, such as linear, quadratic, exponential or modified exponential, were considered in the modelling of energy demand. The bee colony algorithm [7, 8], particle swarm optimization [11], linear programming, evolutionary algorithm [6,9], and neural networks were often used as prediction methods in the research papers [10–13]. Moreover, various short- and long-term scenarios were considered to forecast energy demand in many countries, such as Pakistan, Iran, South Korea and Turkey. The results of computer simulations were compared to current forecasts.

The energy consumption is estimated to double by 2050 compared to 2000. Therefore, even greater attention is being paid to climate change, environmental protection, and CO2 production.

The currently used raw materials are non-renewable, meaning they will eventually run out [3]. Renewable energy sources (RES) such as solar, hydro, and wind are excellent alternatives for energy production, but on a smaller scale. Efforts are underway to reduce the share of conventional power plants in energy production and replace them with non-conventional power plants-wind, hydro, and photovoltaic plants – which utilize renewable energy sources and contribute to environmental protection. The renewable energy sector is currently the most dynamically developing sector of the energy industry in Poland. The share of RES is estimated to increase from the current 6 % to 38 % [1, 2].

Figure 3 presents historical data on socio-economic factors and their trend until 2035.

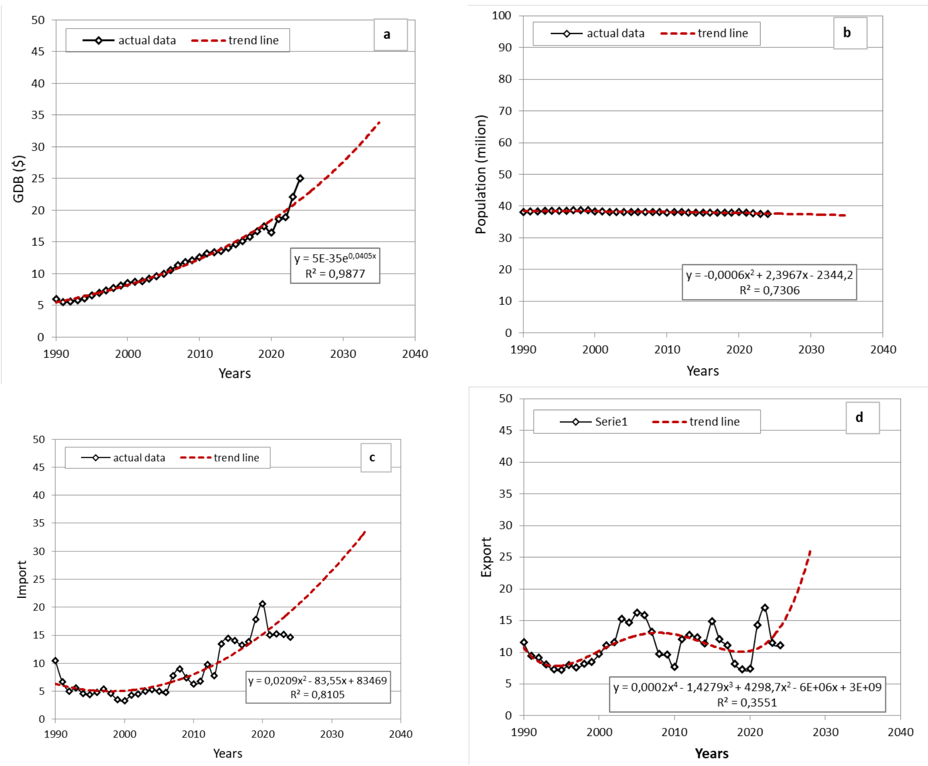


**Figure 3.** The course of the social and economic factors in Poland with the fitted trend lines: a) Gross Domestic Product (GDP per capita, $10^3$ \$), b) population ($10^6$), c) import and d) export (TWh). Source: [19–21].

As shown in Figure 3, there is a dynamic growth in gross domestic product per capita 3a and rising imports of energy (Fig.3c), accompanied by a slight decline in Poland's population (Fig.3b). In the era of globalization and rapid urbanization, significant economic growth is driving the demand for energy in Poland.

## 3 Modelling energy consumption using genetic algorithms

Genetic algorithms (Gas) are an artificial intelligence method based on the principles of natural evolution and selection. The key GA operators are crossover and mutation. Crossover involves the exchange of information between individuals, while mutation involves a change in genotype [15, 16]. GAs have found widespread use in optimizing nonlinear and discontinuous tasks in engineering processes. They are a proven method for finding the global optimum. Genetic algorithms are commonly used for multi-objective optimization tasks [17, 18].

### 3.1 The mathematical models

Electricity consumption was modelled using two mathematical models: the Energy Consumption Quadratic Model (ECQM) and the Energy Consumption Exponential Model (ECEM) (see Figure 1).

The ECQM model takes the following form:

$$ECQM = w_1X_1 + w_2X_2 + w_3X_3 + w_4X_4 + w_5X_1X_2 + w_6X_1X_3 + w_7X_1X_4 + w_8X_2X_3 + w_9X_2X_4 + w_{10}X_3X_4 + w_{11}{X_1}^2 + w_{12}{X_2}^2 + w_{13}{X_3}^2 + w_{14}{X_4}^2 + w_{15} \quad (1)$$

The ECEM model takes the following form:

$$ECEM = w_1{X_1}^{w_2} + w_3{X_2}^{w_4} + w_5{X_3}^{w_6} + w_7{X_4}^{w_8}, \quad (2)$$

where, $X_1, X_2, X_3, X_4$, are the data values: import, export, gross domestic product per capita, and the population in Poland.

### 3.2 Fitness function

The goal of the genetic algorithm (GA) was to find appropriate weights for the models 1-2 so that the mean absolute percent error (MAPE) between the actual energy consumption and the predicted energy consumption was as small as possible (Eq. 3).

$$\min f = \frac{1}{m} \sum_{j=0}^{m} \frac{\left| EC_a - EC_p \right|}{EC_a} \quad (3)$$

The energy modelling was performed in the "Optimization Tool", implemented in Matlab [18]. The model parameters for functions (1-2) were determined (Figure 4).

The data $X_1, X_2, X_3, X_4$, were appropriately normalized from 0 to 1 by dividing them by their maximum values.

### 3.3 Genetic algorithm operators

The most important parameters of the genetic algorithm are population size, number of generations, and crossover and mutation operators. These GA parameters have a significant impact on the optimization process and the simulation results. The effect of population sizes of 60, 80, and 100, and crossover probability (0.7, 0.8, and 0.9) was tested in the study. Finally, a population size of 100 and a crossover probability of 0.8 were selected for the modelling. The generation size and the mutation rate had constant values in the studies. The modelling was made for the function (Equation 3).

## 4 Results of GA simulation

The convergence of the genetic algorithm for the quadratic and exponential models is shown in Figure 4.

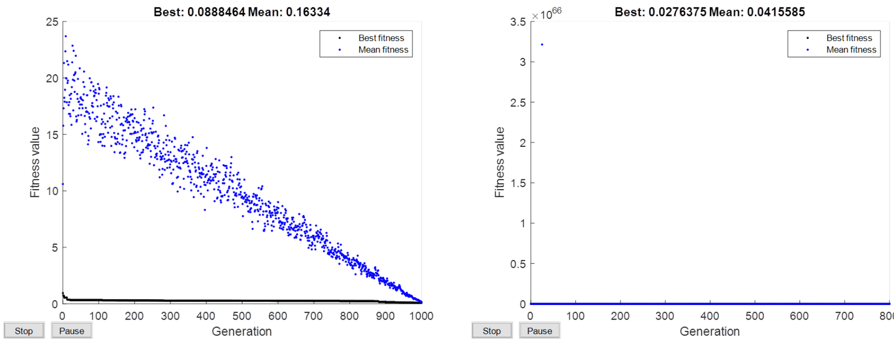


**Figure 4.** The course of the fitness function in the generations: a) EDQM, b) EDEM. Source: own study in Matlab Optimization Toolbox [18].

As can be seen from Figure 4a, the smallest error min $\underline{f} = 0.088$ was obtained for the square model. The model coefficients were: $w_1 = -0.71$; $w_2 = -0.91$; $w_3 = 1.56$; $w_4 = -2.43$; $w_5 = 1.87$; $w_6 = -1.71$; $w_7 = 1.01$; $w_8 = -1.25$; $w_9 = -1.71$; $w_9 = -4.33$; $w_{10} = -1.65$; $w_{11} = -0.43$; $w_{12} = 3.57$; $w_{13} = 1.62$; $w_{14} = -3.48$ *and* $w_{15} = 8.32$.

The weights for the exponential model were also determined: $w_1 = -3.01$; $w_2 = 0.12$; $w_3 = 1.69$; $w_4 = 0.23$; $w_5 = 0.42$; $w_6 = 1.14$; $w_7 = 3.57$; $w_8 = 2.09$. The MAPE $\underline{f}$=0.0276 for the exponential model was achieved as shown in Figure 4b.

As can be seen from Figure 4a, the smallest error, min f = 0.088, was obtained for the square model. The model coefficients were:

The weights for the exponential model were also determined: The MAPE f=0.0276 for the exponential model was achieved as shown in Figure 4b.

As can be seen from Figure 4, the average MAPE changes in the energy consumption values for the exponential model (Fig.4b) were smallest compared to the quadratic model. After finding the best values of the coefficients of the model using GA, the mathematical equations have been formulated:

$$ECQM = -0.71X_1 - 0.91X_2 + 1.56X_3 - 2.43X_4 + 1.87X_1X_2 - 1.71X_1X_3 + 1.01X_1X_4 - 1.25X_2X_3 + -4.33X_2X_4 - 1.65X_3X_4 - 0.43X_1{}^2 + 3.57X_2{}^2 + 1.62X_3{}^2 - 3.48X_4{}^2 + 8.325 \quad (4)$$

$$ECEM = -3.01X_1^{0.12} + 1.69X_2^{0.23} + 0.42X_3^{1.14} + 3.57X_4^{2.09} \quad (5)$$

### 4.1 Results of GA modelling

Figure 5 compares ECQM and ECEM models according to historical data.

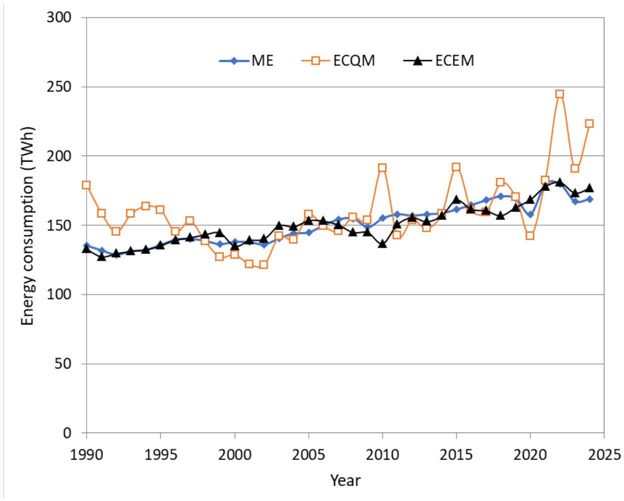


**Figure 5.** Electricity consumption in TWh for various models. Source: own study in Excel.

As shown in Figure 5, the exponential model was similar to the data of Ministry of Energy (ME) model. In comparing the relative error between actual data and estimated, the average relative error was 10.52% and 3.23%, values for quadratic (ECQM) and exponential models (ECEM), respectively. Therefore, the exponential model was selected to determine the electricity consumption projection.

The exponential model ECEM and the polynomial trend curves presented in Figure 3 were used to forecast electricity consumption for each indicator (import, export, GFB per capita, and the population in Poland. A time series approach was then used for each of the socio-economic indicators. The model was used to forecast electricity consumption.The exponential model ECEM and the polynomial trend curves presented in Figure 3 were used to projection electricity consumption for each indicator (import, export, GFB per capita, and the population in Poland. A time series approach was then used for each of the socio-economic indicators. The model was used to forecast electricity consumption.

### 4.2 Results of GA prediction

Forecasting electricity demand is crucial in planning and decision-making regarding the country's power system, the company responsible for electricity supply, and specific areas or groups of customers [22]. Forecasting electricity demand with high accuracy is a challenging task. It is characterized by an indeterminate number of disruptions caused by external factors, which must be considered when making forecasts [23]. Social conditions and culture can also play a role in forecasting. Generally, electricity consumption is characterized by daily, monthly, and annual cycles, which translates into long-term, medium-term, short-term, and ultra-short-term forecasts [24].

The projection of electricity consumption in Poland until 2040 is shown in Figure 6.

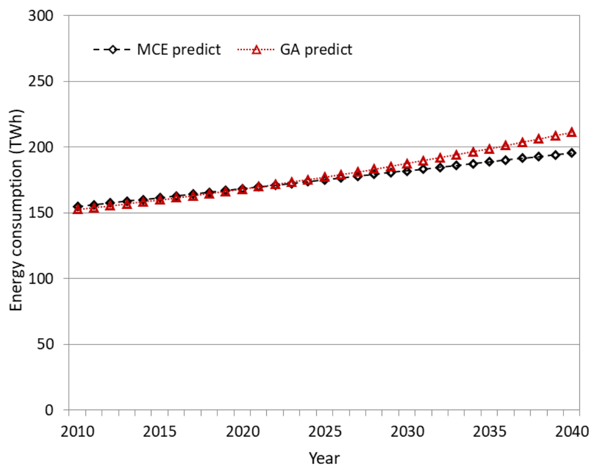


**Figure 6.** The genetic algorithm projection of the energy consumption of Poland. Source: own study.

As can be seen from the graph (Fig.6), the change in energy consumption until 2025 is a similar trend. From 2025, a slight increase in energy consumption can be observed in the model predicted using a genetic algorithm. The electricity forecast conducted using a GA showed an upward trend. The forecast curve is similar to those reported in the data [19–23]. The genetic model forecasts that electricity consumption will gradually increase over the next ten years. The projected GA energy consumption will reach 211 TWh in 2024.

## 5 Conclusions and future research

Genetic algorithms are an effective tool for modelling and forecasting electricity consumption in Poland. The energy consumption model was based on socio-economic indicators such as GDP, population, imports, and exports obtained from 1990 to 2024.

Two models, quadratic and exponential, were proposed to model energy consumption in historical data using a genetic algorithm. The genetic algorithm robustly found appropriate weights for both models. The best mean absolute error was obtained for the exponential model, MAE = 0.0276, for a population size of 100, a crossover probability of 0.85, and a mutation probability of 0.02.

The genetic model forecasts the electricity consumption of 211 TWh by 2040. This indicates a slight increase in energy use compared to the forecasts from the Ministry of

Energy. For comparison purposes, further research could be conducted on the use of artificial neural networks or other intelligent methods to determine the energy consumption.

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