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An experimental fuzzy inference system for the third core module of the first console on the global grid peak power prediction system & its forecasting accuracy measures' comparisons with the first and the second core modules

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Abstract: Our World gives several symptoms of climate change. Devastating draughts increase (negative for World (-)), global mean temperature increase (-), lightning strikes increase (-), sea ice cover melt (-), tree mortality increase (-), and forest degradation increase (-) have been observed for decades. They are all negative measures for continuity of life. Diversity of species has been decreasing, so that life on Earth is dying. Only responsible specie for this situation is humankind. This study presents a small footstep to prevent this situation. Modeling of a 100% renewable power grid on World (Global Grid) is eminent. Annual peak power load (Gigawatt: GW, Kilowatt: kW) (peak demand or load) forecasting in power demand side is crucial for global grid modeling. This study presents an experimental fuzzy inference system for the third core module (100 years' power demand forecasting) of the first console (long term prediction) of Global Grid Peak Power Prediction System (G^2P^3S). The inputs (world population, global annual temperature anomalies °C) and the output (annual peak power load demand of Global Grid in GW) are modeled with seven triangular fuzzy input membership functions and seven constant output membership functions. The constant Sugeno-Type fuzzy inference system is used in the current experimental model. The maximum absolute percentage error (MAP) is calculated as 45%, and the mean absolute percentage error (MAPE) is found as 39% in this experimental study. The MAP and MAPE of the first core module model (Type 1) were 0,46 and 0,36. The MAP and MAPE of the second core module model (Interval Type 2) were 0,46 and 0,36. As a result, this study is a good start for the third core module of the first console on Global Grid Peak Power Prediction System research, development, demonstration, & deployment (RD^3) project. This experimental study also warns humankind in this subject. Hopefully, the most polluting societies on our World such as China, United States, India, Russia, Japan, Germany, South Korea, and Canada take urgent actions to start to build the foundations of 100% renewable power global grid by organizing a global grid consortium.

***Keywords**: Fuzzy inference system, Global grid, Peak power, Scilab, Sugeno, Takagi-Sugeno-Kang,*

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Nomenclature	
APE	Absolute percentage errors
GW	Gigawatt
MAP	Maximum absolute percentage error
MAPE	Mean absolute percentage error

1. INTRODUCTION

Electricity is almost consumed in any activity. Batteries of mobile phones at homes are charged. Lights on the streets are lit. Workbenches and machines at factories are powered. At last, electric vehicles such as cars, high speed trains, trolley-bus, trucks, and ships are charged or powered. All of them consume electricity.

There are two main groups by source in electricity generation. One of them is the non-renewable energy sources (NRES), the other one is the renewable energy sources (RES). NRES technologies consume several kinds of materials as energy sources (e.g. uranium in nuclear power plants, natural gas in combined cycle power plants). In contrast, RES technologies don't consume any material as energy sources, their sources are natural sources (e.g. water for hydropower plants, wind for wind parks, sun for solar power plants). Humankind has consumed many resources for electricity generation until now.

Effects of human activities have been observed by the climate change due to consuming these resources for decades (e.g. forests have died [1,2], food production and drinking water have been threatened [3-6]). Effects of human activities can easily be understood very well [7].

An unavoidable step against the effects of the climate change has already come, which is modeling, designing, constructing and operating a worldwide 100% renewable energy sources power grid (Global Grid). According to the author's perspective, the sooner, the Global Grid is operated, the better, the World will possibly be in the electricity generation field (see clues on [8,9,10,11]). There are already some very well-known publications for large regional grids on the way of the Global Grid (e.g. European Supergrid [12], Supergrid Concept for America [13], DESERTEC [14], Gobitec [15,16], Asian Super Grid Concept [15,16], Global Grid Concept [17]). The definition of the Global Grid is "a grid spanning the whole planet and connecting most of the large power plants in the world" [17]. All continents (Africa, Antarctica, Asia, Australia, Europe, North America, and South America) and all renewable power sources (geothermal, hydro, solar, wave, and wind) will be connected to each other in this grid (Fig.1.).

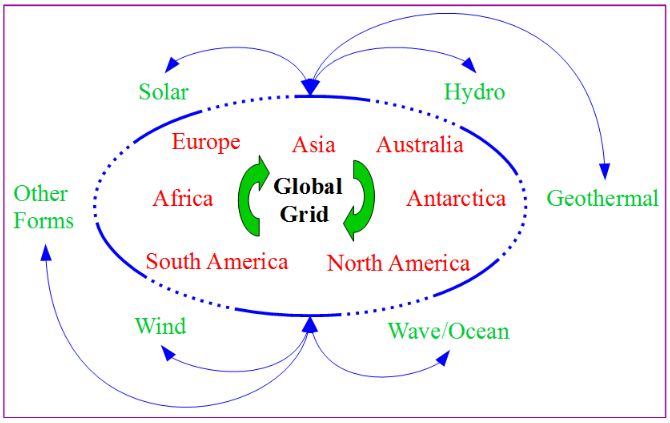

Figure 1. Global Grid approach (drawn based on information see [17], generated by the Apache Open Office 4.1.1 & the Paint.NET Version 4.0.19)

One of the modeling challenges of the Global Grid is the accurate forecasting of the power load demand (peak power load). The power load demand in this study is accepted as the annual peak power load/demand (in Gigawatt: GW). This amount is important, because the total installed power of all plants (disposable) must be larger than this amount on a timely basis. Otherwise, power outage (cut, blackout, failure) will occur in the Global Grid. Hence, the annual peak power load/demand must be predicted on the annual basis in very early studies. This study, which is a small part of a lifelong research, development, demonstration, & deployment (RD^3) project, aims to handle this problem by a forecasting (projection, prediction) module of a forecasting (projection, prediction) system (Global Grid Peak Power Prediction System) (see [18]).

This forecasting should be made in several time horizons. They might be divided into four categories as very short, short, medium and long term (range or run) [19-23]. This research study is grouped under the long-range forecasting with a period of 100 years, so that the findings can be used for the Global Grid expansion plans (strategic planning) (see [22,23]). The Global Grid goals, the power plants' capacities, and the development plans shall all be related to the long run forecasting studies [see 22,23]. This long-range forecasting with a period of 100 years will automatically be performed by several modules of the long-term forecasting (projection, prediction) console (first console) of the proposed system (see [18]). This study researches on one of the core modules (third core module).

The following section presents the literature review. The experimental fuzzy inference system (FIS) and its first experimental analysis based on the worldwide data is presented in Section 3. The conclusions and planned research studies are presented in Section 4.

2. LITERATURE REVIEW & BACKGROUND

This literature review was performed from 11th of June 2015 to 01st of July 2015. Some key terms were searched to find the previous studies on some academic publications' database websites. The key terms and their hits number for directly related studies (not only peak power, but also electricity demand) were presented in Table 1 for easy and accurate information. Only journal and conference papers, and books were reviewed in this study. It was observed that only 3 academic publications' database websites were presented a major number of studies in this subject. ACM Digital Library, Springer and some other popular academic search engines were very useful with key terms such as "Fuzzy Inference System" and" Electricity", "Fuzzy Inference System" and "Forecast", and "Fuzzy Inference System" and "Demand". This review showed that fast and appropriate literature review in this study could be performed on these 3 academic publications database websites with these key terms in the following research studies.

Table 1. Literature review summary (more than 5 studies in color background)

	1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**	**14**	**15**
1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
3	0	0	0	0	0	0	3	0	0	0	0	0	0	0	0
4	0	0	0	0	0	0	2	0	0	0	0	0	0	0	0
5	0	0	0	0	0	0	3	0	0	0	0	0	0	0	0
6	0	0	0	0	0	0	3	0	0	0	0	0	0	0	0
7	16	0	0	1	1	0	84	0	1	0	0	25	4	0	0
8	19	0	0	0	3	0	77	0	0	0	0	20	2	1	1
9	20	0	0	1	1	0	64	0	1	0	0	18	3	3	1
10	21	0	0	0	1	0	186	0	1	0	0	16	2	2	1
11	20	0	0	1	1	0	190	0	1	0	0	10	0	2	1
12	21	0	0	0	0	0	163	0	1	0	0	16	3	2	1
13	0	0	0	0	0	0	3	0	0	0	0	0	0	0	0
14	0	0	0	0	0	0	8	0	0	0	0	0	0	0	0
15	1	0	0	0	0	0	10	0	0	0	0	1	0	0	0
16	0	0	0	0	0	0	12	0	0	0	0	0	0	0	0
17	0	0	0	0	0	0	10	0	0	0	0	0	0	0	0
18	0	0	0	0	0	0	8	0	0	0	0	0	0	0	0
19	0	0	0	0	0	0	2	0	0	0	0	0	0	0	0
20	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0
21	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
22	0	0	0	0	0	0	2	0	0	0	0	0	0	0	0
23	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
24	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0

(final review date: 01st of July 2015; key terms: (1) Fuzzy Logic Inference System and Electricity, (2) Fuzzy Logic Inference System and Forecast, (3) Fuzzy Logic Inference System and Demand, (4) Fuzzy Logic Inference System and Electricity and Forecast, (5) Fuzzy Logic Inference System and Electricity and Demand, (6) Fuzzy Logic Inference System and Electricity and Forecast and Demand, (7) Fuzzy Inference System and Electricity, (8) Fuzzy Inference System and Forecast, (9) Fuzzy Inference System and Demand, (10) Fuzzy Inference System and Electricity and Forecast, (11) Fuzzy Inference System and Electricity and Demand, (12) Fuzzy Inference System and Electricity and Forecast and Demand, (13) Fuzzy Control System and Electricity, (14) Fuzzy Control System and Forecast, (15) Fuzzy Control System and Demand, (16) Fuzzy Control System and Electricity and Forecast, (17) Fuzzy Control System and Electricity and Demand, (18) Fuzzy Control System and Electricity and Forecast and Demand, (19) Fuzzy Rule System and Electricity, (20) Fuzzy Rule System and Forecast, (21) Fuzzy Rule System and Demand, (22) Fuzzy Rule System and Electricity and Forecast, (23) Fuzzy Rule System and Electricity and Demand, (24) Fuzzy Rule System and Electricity and Forecast and Demand, academic database websites: 1: ACM Digital Library, 2: ASCE Online Research Library, 3: American Society of Mechanical Engineers, 4: Cambridge Journals Online, 5: Directory of Open Access Journals, 6: Emerald Insight, 7: Other Popular Academic Search Engine, 8: Hindawi Publishing Corporation, 9: Inderscience Publishers, 10: Journal of Industrial Engineering and Management, 11: Science Direct, 12: Springer, 13: Taylor & Francis Online/Journals, 14: Wiley-Blackwell/Wiley Online Library, 15: World Scientific Publishing)

In this review, it was understood that forecasting studies on the electrification systems were usually grouped according to their time horizons in four groups (i.e. real time/very short term [24], short term [25], medium term [26] and long term [27]) studies (see [28]). There were more than 40 documents in the long term electricity demand (e.g. kWh, MWh, GWh in units) and power demand (e.g. kW, MW, GW in units) in this review. Al-zahra et.al. (2015) studied the monthly electrical consumption in Basra (January 2005 to December 2011) by Auto-Regressive Integrated Moving Average (ARIMA) model and two layered feed forward artificial neural network (ANN) with 12 neurons in the hidden layer, and finally an adaptive neuro-fuzzy inference system (ANFIS) model [29]. They managed the mean absolute errors (MAE) of 0,31604 (Box-Jenkins ARIMA), 0,301 (ANN), and 0,2491 (ANFIS) [29]. Arfoa (2015) studied the maximum load (2005 to 2013) (MW) and forecasted peak load demand (2014 to 2023) in Ma'an, Karak and Aqaba in Jordan by least squares method [27]. Demir (2014) studied load (MW) in the Northern-Iraq by Winters' additive (5,7% Mean absolute percentage error: MAPE) and seasonal ARIMA (SARIMA) (5,4%) models [30]. Hong (2009) worked with a support vector regression (SVR) model for load forecasting (MW) of four regions in Taiwan [31]. The MAPE was found between 1,29% and 2,45% for different regions. Yan and Yang (2012) developed a fuzzy load forecasting model [32]. Most of the remaining studies were aimed to forecast the electricity demand (e.g. kWh, MWh.). Some of these studies weren't clear enough for either their scope or their units (MW or MWh). Moreover, some of these studies presented some unidentified units such as symbolized by kW/h (kilowatt per hour).

This literature review showed that the power load (peak load) forecasting was studied by some researchers, however nobody worked on the power load (peak load) long term forecasting of the Global Grid Concept or any super grid models. This study will be beyond the usual applications, not only because of the Global Grid Peak Power Prediction System (G^2P^3S), but also the forecasting horizon as long term: 100 years (see [18]). It is thought that the "experimental" word presents this situation very well.

This research paper is the successor of the previous publications (see [33-36]) about the Global Grid Prediction Systems (G^2PS) that consists of the Global Grid Electricity Demand Prediction System (G^2EDPS) major unit and the Global Grid Peak Power Prediction System (G^2P^3S) major unit. All of them present the research, development, demonstration, & deployment (RD^3) efforts, progresses and interim findings of only one unique global system, Global Grid Prediction Systems (G^2PS), Global Grid Electricity Demand Prediction System (G^2EDPS) and Global Grid Peak Power Prediction System (G^2P^3S) (see [18]).

The 1st core module and its 10 extension modules in the 1st console (long term prediction) of Global Grid Electricity Demand Prediction System (G^2EDPS) is presented in 2017 (research findings in 2015) [35], some core module approaches in the 1st console of Global Grid Electricity Demand Prediction System (G^2EDPS) is presented in 2017 [34], the basic ideas of 1st and 2nd core modules in the 1st console (long term prediction) of Global Grid Peak Power Prediction System (G^2P^3S) is presented in 2017 [33]. This research study can be grouped in the 3th core module in the 1st console of Global Grid Peak Power Prediction System (G^2P^3S). The simplistic presentation of the current study is given by Fig.2.

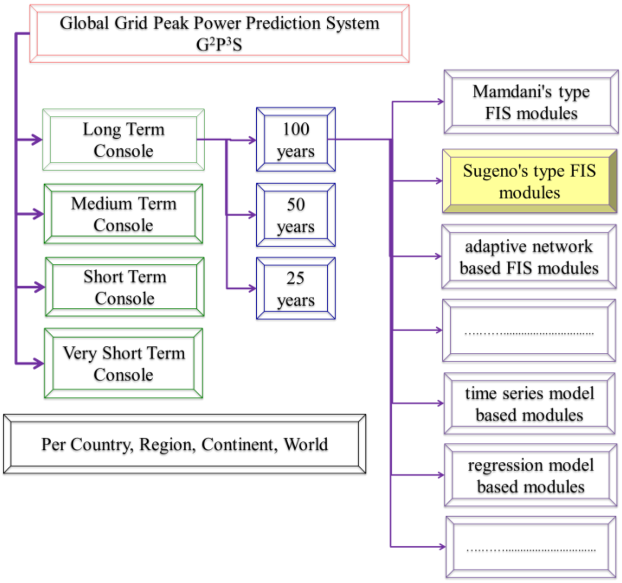

Figure 2. Simplistic overview of this study (generated by the Microsoft Office Powerpoint 2007)

3. EXPERIMENTAL SUGENO TYPE FUZZY INFERENCE SYSTEM (FIS) FOR GLOBAL GRID PEAK POWER PREDICTION SYSTEM (G^2P^3S) THIRD CORE MODULE

The experimental power load (peak load) forecasting of the Global Grid is modeled based on two inputs and one output in an one node Sugeno or Takagi-Sugeno-Kang (TSK)'s type fuzzy inference system (FIS) (fuzzy control system, fuzzy rule base system, or fuzzy expert system) (Fig.3).

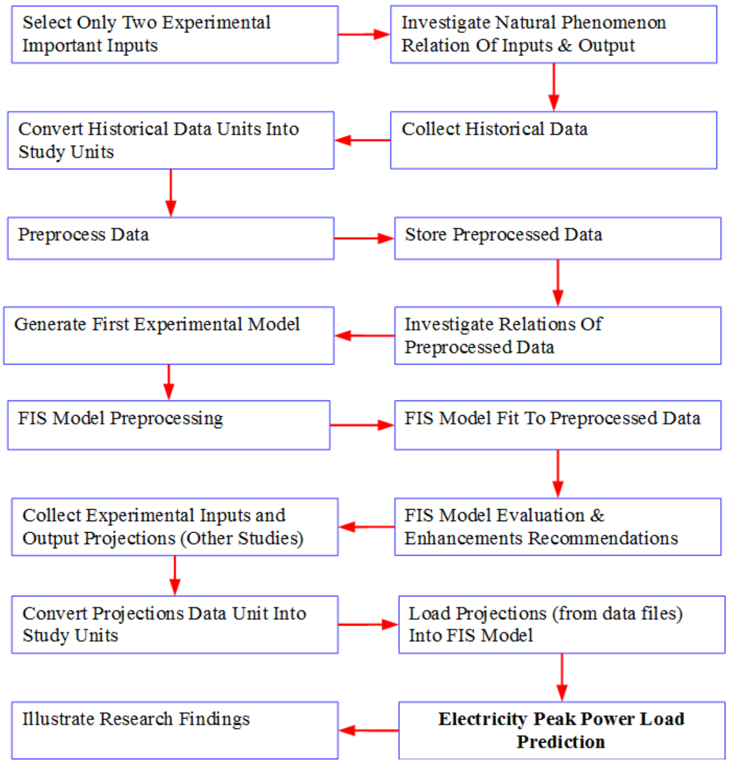

Figure 3. The experimental one node Sugeno or Takagi-Sugeno-Kang (TSK) type Fuzzy Inference System (FIS) for electricity peak power load forecasting of Global Grid Concept (visualization generated by the flow diagram of the Apache OpenOffice 4.1.1 Draw & the Paint.NET Version 4.0.19).

The Sugeno or Takagi-Sugeno-Kang (TSK) type fuzzy inference engine (linear or constant: constant) is preferred in this first experimental model, although the Mamdani type fuzzy inference engine is presented as having better representation of human cognition (nonlinear approximation) (see [37-39]). The Sugeno or Takagi-Sugeno-Kang (TSK) fuzzy inference systems are one of the most common fuzzy inference system types that can solve one of the main difficulties of completely "computing with words". The Sugeno or Takagi-Sugeno-Kang (TSK) fuzzy inference systems use the rules in the linear function approximation form such as follows *"IF the speed x of a car is high, THEN the force to the accelerator is y = cx"* or in the more formal form *"IF x_1 is C_1^l and ..... and x_n is C_n^l, THEN $y^l = c_0^l + c_1^l x_1 + ... + c_n^l x_n$"* ($C_i^l$: fuzzy sets, c_i^l: constants, l = 1,2, ..., M) [40-43].

This experimental model is developed as the simplest and easiest model at this research, development, demonstration, & deployment (RD^3) stage, so that two inputs (factor, index, measure, or variable) are selected as the global population (world population) and the global land ocean annual mean temperature change (global annual temperature anomalies) and one output is selected as the annual peak power demand.

The first variable (X_1) is selected as the world population. The author thinks that the peak power load demand is strongly related to the population (cognitive approximation), because humans consume electricity, not animals and plants. Hence, the world population and the peak power load demand have to be investigated together according to author's mental model in today's conditions (in the past and in future non-similar conditions, e.g. chaotic key minerals and resources run out conditions in future like going back to the stone age). The historical data are collected from the Department of Economic and Social Affairs of the Population Division in the United Nations (see Fig.4 top left). The R Version 3.2.2 linear model fitting analysis is also performed on the R Studio Version 1.0.136 to understand the character of the first variable (X_1) (see line in red color on Fig.4 top left) and the model is gathered as in Equation 1 (see [44-47]).

$$\textit{World Population} = (-146234895{,}78) + (76155{,}54) \times \textit{Year (Adjusted } R^2\textit{: 0,9954)} \quad (1)$$

The R Version 3.2.2 and R Studio Version 1.0.136 scripts are presented in Appendix 1.

The forecasted data for the first variable (X_1) is also taken from the same website. The forecast of this variable is presented on the webpage from 2010 to 2100 for each 5 years' period (2010, 2015, 2020, ..., 2100) (no approximation and curve fitting in this study) (see Fig.4 top right). According to these data, the forecasting intervals of this study is at first taken as 5 years (see other input variable as 10 years for final decision in this study). The R Version 3.2.2 linear model fitting analysis is also performed on the R Studio Version 1.0.136 to understand the character of the first variable forecasts better (X_1) (see line in red color on Fig.4 top left) and the model is gathered as in Equation 2 (see [44-47]).

$$\textit{World Population Prediction} = (-78810091{,}40) + (42938{,}99) \times \textit{Year (Adjusted } R^2\textit{: 0,9385)} \quad (2)$$

The R Version 3.2.2 and R Studio Version 1.0.136 scripts are presented in Appendix 1.

The second variable (X_2) is selected as the global annual temperature anomalies (degrees Celsius: °C). The data are gathered from the official webpage of the NASA Goddard Institute for Space Studies (GISS) Laboratory in the Earth Sciences Division (ESD) of National Aeronautics and Space Administration's (NASA) Goddard Space Flight Center (GSFC) (see Fig.4 middle top left). The R Version 3.2.2 linear model fitting analysis is also performed on the R Studio Version 1.0.136 to understand the character of the second variable (X_2) (see line in red color on Fig.4 middle top left) and the model is gathered as in Equation 3 (see [44-47]).

$$\textit{Global Annual Temperature Anomalies} = (-13.025855461) + (0.006688811) \times \textit{Year (Adjusted } R^2\textit{: 0,7677)} \quad (3)$$

The R Version 3.2.2 and R Studio Version 1.0.136 scripts are presented in Appendix 1.

The projection data for the second variable (X_2) are gathered from the Intergovernmental Panel on Climate Change, Annex II: Climate System Scenario Tables, Table AII.7.5. All of the forecast data in each projection RCP2.6 (95%), RCP4.5 (95%), RCP6.0 (95%), RCP8.5 (95%), and SRES A1B (95%) are taken into account. They are presented for each 10 years period from 2010 to 2100 (see Fig.4 middle top right). According to this data, the forecasting intervals of this study is at last taken as 10 years instead of 5 years according to the other input variable. The R Version 3.2.2 linear model fitting analysis is also performed on the R Studio Version 1.0.136 to understand the character of the second variable projection (X_2) (see line in red color on Fig.4 middle top right) and the model is gathered as in Equation 4-8 (see [44-47]).

Global Annual Temperature Anomalies Projection RCP2.6= (-22.18909091)+(0.01152121) ×Year (Adjusted R2: 0,7625) (4)

Global Annual Temperature Anomalies Projection RCP4.5=(-47.77290909)+(0.02414545)×Year (Adjusted R2: 0,9356) (5)

Global Annual Temperature Anomalies Projection RCP6.0=(-66.80127273)+(0.03349697)×Year (Adjusted R2: 0,9954) (6)

Global Annual Temperature Anomalies Projection RCP8.5=(-109.33618182)+(0.05457576)×Year (Adjusted R2: 0,9911) (7)

Global Annual Temperature Anomalies Projection SRES.A1B=(-82.01436364)+(0.04108485)×Year (Adjusted R2: 0,9979) (8)

The R Version 3.2.2 and R Studio Version 1.0.136 scripts are presented in Appendix 1.

The output (Y) is the annual peak power load demand of the Global Grid. The historical data can't be found in any official records during this study. An approximation based on some practical life experience related assumption is made under this situation. The historical total electricity installed capacity (million kilowatts) data is gathered from the official records at the U.S. Energy Information Administration. The unit conversion is first made from kilowatts to gigawatts (1 kW = 10^{-6} GW). Afterwards, 60% of these amounts are accepted as the annual peak power load demand based on the expert experience, recommendation and opinion in the practical power industry engineering field applications. This assumption will be investigated in detail in the future research studies related to this study. The world data is taken into account in the data file (see Fig.4 middle bottom left). The R Version 3.2.2 linear model fitting analysis is also performed on the R Studio Version 1.0.136 to understand the character of the output (Y) (see line in red color on Fig.4 middle bottom left) and the model is gathered as in Equation 9 (see [44-47]).

Annual Global Peak Power Demand (GW)=(-116963.22139)+(59.60695)×Year (Adjusted R2: 0.9444) (9)

The R Version 3.2.2 and R Studio Version 1.0.136 scripts are presented in Appendix 1.

Above all, a very simple statistical data analysis on the R Version 3.2.2 and the R Studio Version 1.0.136 is also performed for X_1 (1950−2010) (world population) and Y (1980−2012) (analysis: 1980−2010) (annual peak power load) together (see Fig.4 middle bottom right), X_2 (1880−2014) (global annual temperature anomalies) and Y (1980−2012) (analysis: 1980−2012) (annual peak power load) together (see Fig.4 bottom left), X_1 (1950−2010) and X_2 (1880−2014) (analysis: 1950−2010) together on the historical values (see Fig.4 bottom right) (see [44-47]) to understand the character of these variables with each other (see line in red color on figures). The R Version 3.2.2 linear model fitting analysis is performed on the R Studio Version 1.0.136 (see line in red color on Fig.4) and the model is gathered as in Equation 10-12 (see [44-47]).

Annual Global Peak Power Demand (GW)=(-1.883384e+03)+(6.684671e-04)×World Population (Adjusted R2: 0.9461) (10)

Annual Global Peak Power Demand (GW)=(994.469)+(2391.610)×Global Annual Temperature Anomalies (Adjusted R2: 0.7046) (11)

$$\text{Global Annual Temperature Anomalies}=(8.103186e\text{-}01)+(2.106483e\text{-}07)\times\text{World Population (Adjusted R2: 0.745)} \tag{12}$$

The R Version 3.2.2 and R Studio Version 1.0.136 scripts are presented in Appendix 1.

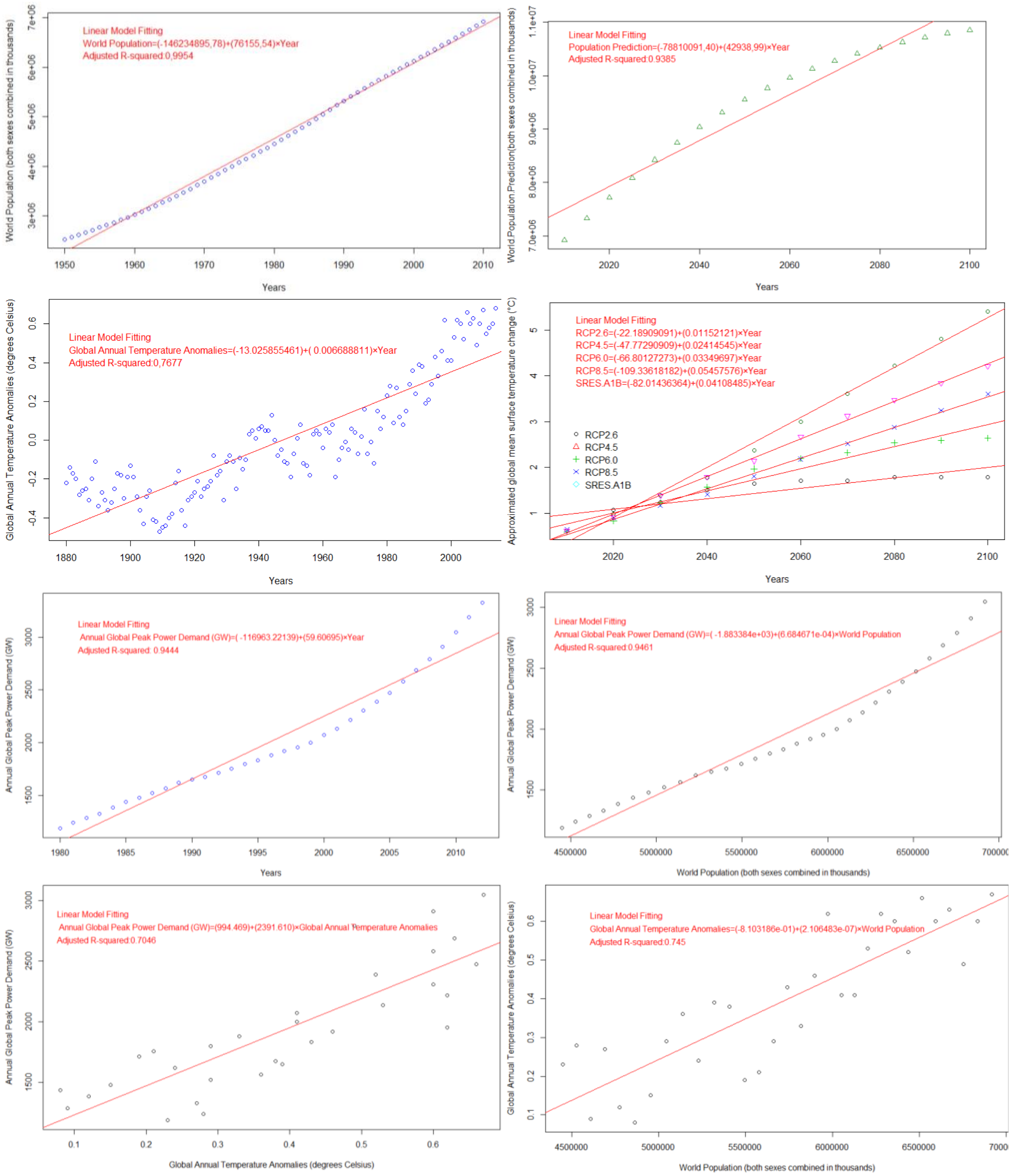

Figure 4. Inputs and outputs (historical X_1 (top left), projection X_1 (top right), historical X_2 (middle top left), projection X_2 (middle top right), historical Y (middle bottom left), historical X_1 & historical Y (middle bottom right), historical X_2 & historical Y (bottom left), historical X_1 & historical X_2 (bottom right)) visualization generated by the scatter graph with fitted linear model straight lines of the R Version 3.2.2 and the R Studio Version 1.0.136 & the Paint.NET Version 4.0.19 (see also Appendix 1).

Moreover, a simple linear multivariable regression model for the variables X_1, X_2, and Y on the R Version 3.2.2 and the R Studio Version 1.0.136 is also built and tested on the historical values (Fig.5) (multiple or multivariate regression). The residuals vs fitted plot with the current pattern and red line shows that the linearity assumption isn't met on this model (see Fig.5 top left). A perfectly flat red line is ideal on the residuals vs fitted plot ([44-47]). The normal Q-Q with its curved shape also shows the same phenomenon (see Fig.5 bottom left). When the residuals are normally distributed the dots presents a straight line on the normal Q-Q ([44-47]). The scale-location plot with its red line and dots form indicates the same phenomenon (see Fig.5 top right). A horizontal line with equally spreading points is ideal on the scale-location plot ([44-47]). The residuals vs leverage plot presents no major influential case, because of the far 0,5 red dashed Cook's distance line (see Fig.5 bottom right). The ideal residuals vs leverage plot is a plot with that a smooth red line close to the horizontal gray dashed line and plots without large Cook's distances ([44-47]). The R Version 3.2.2 model fitting analysis is performed on the R Studio Version 1.0.136 and the model is gathered as in Equation 13 (see [44-47]).

$$\text{Annual Global Peak Power Demand (GW)}=(-1.882294e+03)+(6.681837e-04)\times \text{World Population} + (1.345441e+00)\times \text{Global Annual Temperature Anomalies (Adjusted R2: 0.9441, Multiple R2: 0.9479)} \quad (13)$$

The R Version 3.2.2 and R Studio Version 1.0.136 scripts are presented in Appendix 1.

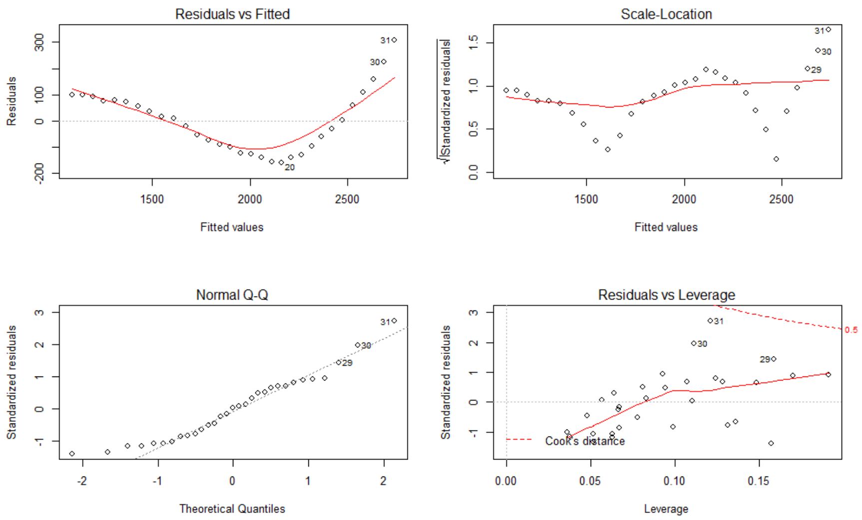

Figure 5. Diagnostic plots of the historical X_1 & X_2 & Y linear model, visualization generated by the scatter graph with fitted linear model straight lines and diagnostic plots of the R Version 3.2.2 and the R Studio Version 1.0.136 & the Paint.NET Version 4.0.19 (see also Appendix 1).

The readers should visit some of the following references for the R statistical analysis (e.g. [44-47]).

The analysis is interpreted by the author as that the FIS can be helpful in this subject. This interpretation will be checked in the future research studies. As a result, the author thinks that trying to model this problem with a Sugeno or Takagi-Sugeno-Kang (TSK) type inference engine will be worthwhile. The data set is studied and the modeling period should be from 1980 to 2010 (31 years) and forecasting period is from 2011 to 2100 (90 years) with the intervals of 10 years (prediction for 2020, 2030,..., 2100). The inputs are modeled by seven triangular membership functions according to the simplistic approximation approach based on the status of expert opinion and judgments (see Script for 5.4.1 in Appendix 2 and Fig.6). The core modelling philosophy due to the cognitive reasons is the magical number 7, 7±2 rule (see [48,49]). The output is modeled by constant membership functions according to the simplistic approximation approach based on the status of expert opinion and judgments (see Script for 5.4.1 and Fig.6). The minimum and maximum values in the data set are considered and split into same membership functions. The rule base is modelled as 49 rules (fixed, permanent) according to the expert current opinion and judgments (see Appendix 3). The readers should visit some of the important studies for the FIS modeling (e.g. [40,42]). The Fuzzy Toolbox 0.4.6 on the Scilab 5.5.2 is used in this study.

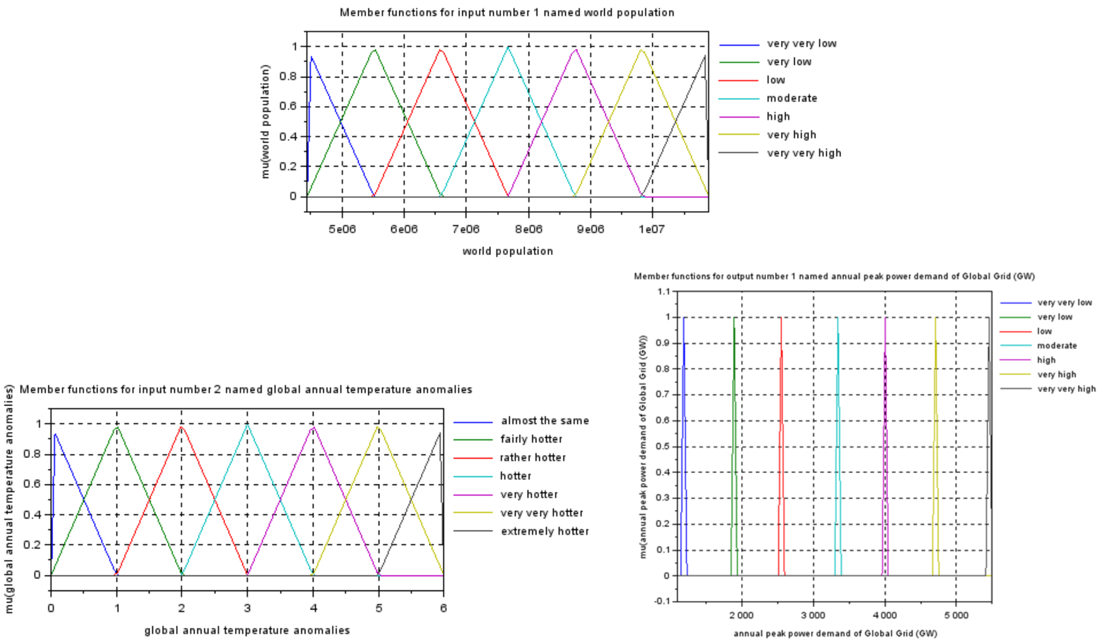

Figure 6. Membership functions X_1 (top left), membership functions X_2 (top right), membership functions Y (bottom left), Scilab 5.5.2 Fuzzy Toolbox 0.4.6 & Paint.NET (see also Appendix 2 & 3).

A few prediction performance assessments are tested in this experimental study.

Absolute percentage errors (APE):

$$APE_t = \frac{(|Actual_t - Predicted_t|)}{(Actual_t)} \qquad (14)$$

Maximum absolute percentage error (MAP):

$$MAP = max(APE_t) \qquad (15)$$

Mean absolute percentage error (MAPE):

$$MAPE = \frac{1}{n}\sum_{1}^{n}(APE_t) \qquad (16)$$

Forecast Errors:

$$e_t = Actual_t - Predicted_t \text{ or } e_t = Predicted\ Model\ 1_t - Predicted\ Model\ 2_t \qquad (17)$$

where Actual: historical annual electricity demand of Global Grid, predicted: forecasted annual electricity demand of Global Grid, t: year, and n: total number of years.

The APE_t are as 0,42; 0,42; 0,41; 0,41; 0,41; 0,41; 0,40; 0,39; 0,39; 0,38; 0,37; 0,36; 0,36; 0,35; 0,35; 0,35; 0,35; 0,34; 0,34; 0,34; 0,35; 0,35; 0,37; 0,38; 0,39; 0,39; 0,41; 0,42; 0,43; 0,44; 0,45 for 1980 to 2010. The MAP is 0,45. The MAPE is 0,39.

The findings of this experimental model are compared with the experimental core type 1 Mamdani FIS based Global Grid peak power load forecasting model (ECT1MFISGGPP) (see [33]) and experimental core interval type 2 Mamdani FIS based Global Grid peak power load forecasting model (ECIT2MFISGGPP) (see [33]) on historical data (Table 2 & Table 3). The MAP and the MAPE of the experimental core type 1 Mamdani FIS based Global Grid peak power load forecasting model

(ECT1MFISGGPP) is respectively 0,46 and 0,36. The MAP and the MAPE of the experimental core interval type 2 Mamdani FIS based Global Grid peak power load forecasting model (ECIT2MFISGGPP) is respectively 0,46 and 0,36.

Table 2. Comparison of actual, 1st, 2nd and 3rd core module predictions

Year	Historical Peak Power (GW)	First Core Module: Experimental Core Type 1 Mamdani Fuzzy Logic Inference System Annual Global Peak Power Demand Predictions (GW)	Second Core Module: Experimental Core Interval Type 2 Mamdani Fuzzy Logic Inference System Annual Global Peak Power Demand Predictions (GW)	Third Core Module: Experimental Core Constant Sugeno-Type Fuzzy Logic Inference System Annual Global Peak Power Demand Predictions (GW)
1980	1983	1337	1304	1156
1981	2071	1391	1381	1207
1982	2147	1450	1418	1260
1983	2217	1511	1506	1314
1984	2313	1572	1527	1369
1985	2399	1630	1572	1425
1986	2471	1683	1678	1484
1987	2542	1730	1798	1543
1988	2611	1767	1814	1604
1989	2702	1796	1822	1664
1990	2754	1816	1829	1722
1991	2797	1828	1832	1780
1992	2858	1833	1834	1836
1993	2928	1865	1868	1890
1994	3000	1911	1913	1944
1995	3055	1962	2004	1996
1996	3135	2018	2010	2048
1997	3202	2076	2114	2098
1998	3258	2136	2106	2148
1999	3338	2198	2193	2197
2000	3457	2260	2280	2247
2001	3560	2320	2272	2297
2002	3697	2378	2369	2346
2003	3846	2433	2407	2397
2004	3983	2483	2367	2447
2005	4123	2528	2519	2498
2006	4303	2568	2564	2549
2007	4478	2607	2613	2605
2008	4650	2653	2811	2661
2009	4852	2706	2729	2718
2010	5081	2764	2753	2775

(Source: First Core Module: Experimental Core Type 1 Mamdani Fuzzy Logic Inference System Annual Global Peak Power Demand Predictions & Second Core Module: Experimental Core Interval Type 2 Mamdani Fuzzy Logic Inference System Annual Global Peak Power Demand Predictions (GW) [33])

Table 2. Forecast errors of 1st, 2nd and 3rd core module predictions

Year	Forecast Errors Of 1st Core	Forecast Errors Of 2nd Core	Forecast Errors Of 3rd Core	Forecast Errors Of 1st & 3rd Core	Forecast Errors Of 2nd & 3rd Core
1980	646	679	827	181	148
1981	680	690	864	184	174
1982	697	729	887	190	158
1983	706	711	903	197	192
1984	741	786	944	203	158
1985	769	827	974	205	147
1986	788	793	987	199	194

1987	812	744	999	187	255
1988	844	797	1007	163	210
1989	906	880	1038	132	158
1990	938	925	1032	94	107
1991	969	965	1017	48	52
1992	1025	1024	1022	-3	-2
1993	1063	1060	1038	-25	-22
1994	1089	1087	1056	-33	-31
1995	1093	1051	1059	-34	8
1996	1117	1125	1087	-30	-38
1997	1126	1088	1104	-22	16
1998	1122	1152	1110	-12	-42
1999	1140	1145	1141	1	-4
2000	1197	1177	1210	13	33
2001	1240	1288	1263	23	-25
2002	1319	1328	1351	32	23
2003	1413	1439	1449	36	10
2004	1500	1616	1536	36	-80
2005	1595	1604	1625	30	21
2006	1735	1739	1754	19	15
2007	1871	1865	1873	2	8
2008	1997	1839	1989	-8	150
2009	2146	2123	2134	-12	11
2010	2317	2328	2306	-11	-22

(Source: First Core Module: Experimental Core Type 1 Mamdani Fuzzy Logic Inference System Annual Global Peak Power Demand Predictions & Second Core Module: Experimental Core Interval Type 2 Mamdani Fuzzy Logic Inference System Annual Global Peak Power Demand Predictions (GW) [33])

Although this first TSK type FIS model isn't able to present the real world situation very well (zero error measures target), these results and findings show that the lifelong research, development, demonstration, & deployment (RD^3) project efforts of this system is worthwhile. This model should be improved for getting better predictions. The long term forecasts (100 years) are presented in Fig.7 (see also Appendix 4).

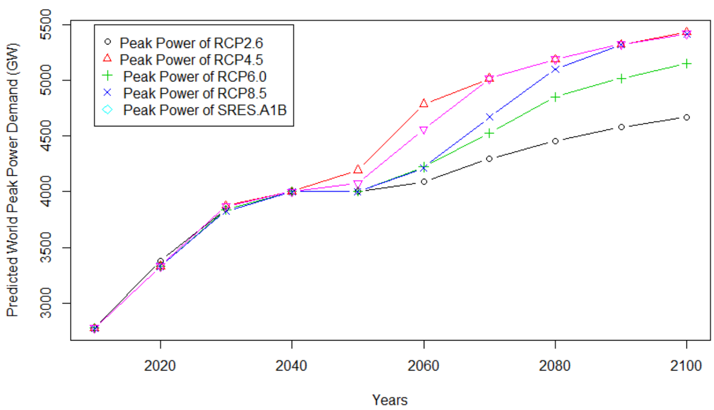

Figure 7. Projection Y visualization generated by the R and the R Studio & the Paint.NET (see also Appendix 4).

4. CONCLUSION and FUTURE WORK

The major scientific contribution of this research study is its ability and representation of the problem definition and the new proposed system (Global Grid Prediction Systems (G^2PS), Global Grid Electricity

Demand Prediction System (G^2EDPS) and Global Grid Peak Power Prediction System (G^2P^3S) (see [18]). The importance of the forecasting peak power load demand the Global Grid is clearly underlined. A research, development, demonstration, & deployment (RD^3) program for developing a Global Grid Peak Power Prediction System (G^2P^3S) by different approaches for several forecasting periods in several modules is mainly started by this study. There are two inputs (world population and global annual temperature anomalies °C). The natural cause and effect of the world population and the annual peak power load demand of the Global Grid is clearly expressed (input output natural relation). The natural cause and effect of the global annual temperature anomalies and the annual peak power load demand of the Global Grid is still under investigation for expressing with words and sentences in a very easy manner, despite the fact of expressing of the relation between the temperature increase and the heating, ventilation and air conditioning electricity consumption increase on annual basis. Only two input variables are preferred because other possible variables are still under investigation (tens of variables or hundreds of variables). It is believed that a good presentation of possible usage of the Sugeno or Takagi-Sugeno-Kang (TSK) type FIS engine is performed in this study. The necessity of improvements of the current model is also clearly mentioned. The author thinks that an artificial neural network (ANN) embedded FIS model will be a great contribution. The author plans to improve this experimental model by a multi mode FIS at first and followed by an adaptive neuro-fuzzy inference system (ANFIS) for the peak power load demand forecasting of the Global Grid by the help of the Scilab and the Scicos.

The whole research, development, demonstration, & deployment (RD^3) studies and publications, and also the conceptual design stage of Global Grid Prediction Systems (G^2PS), Global Grid Electricity Demand Prediction System (G^2EDPS) and Global Grid Peak Power Prediction System (G^2P^3S) shall be developed under the Open Source Initiative and the Free Software Foundation approaches. This act will hopefully increase not only the interest of coding and scripting efforts of the young researchers, but also the contribution of the experienced researchers. The revolution on the World with this initiative will surely be experienced with the Apache OpenOffice, the Carrot2, the Gephi, the Juzzy, the Paint.NET, the Python, the R, the R Studio, the Scilab, the WinMerge and others. It is hoped that engineers from all over the world will join to this project and contribute to the research, development, demonstration, & deployment efforts of this system.

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APPENDIX 1

R Scripts of Figure 4 & 5
world population historical X_1 & Year

```
****************************************************************************************************
world population historical X1 (country code: 900, year: 1950-2010: 61 data, access date: 05/07/2015)
Year=c(1950,1951,1952,1953,1954,1955,1956,1957,1958,1959,1960,1961,1962,1963,1964,1965,1966,1967,1968,1969,1970
    ,1971,1972,1973,1974,1975,1976,1977,1978,1979,1980,1981,1982,1983,1984,1985,1986,1987,1988,1989,1990,199
    1,1992,1993,1994,1995,1996,1997,1998,1999,2000,2001,2002,2003,2004,2005,2006,2007,2008,2009,2010)
World.Population=c(2525779,2572851,2619292,2665865,2713172,2761651,2811572,2863043,2916030,2970396,3026003,3
    082830,3141072,3201178,3263739,3329122,3397475,3468522,3541675,3616109,3691173,3766754,3842874,39191
    82,3995305,4071020,4146136,4220817,4295665,4371528,4449049,4528235,4608962,4691560,4776393,4863602,4
    953377,5045316,5138215,5230452,5320817,5408909,5494900,5578865,5661086,5741822,5821017,5898688,59753
    04,6051478,6127700,6204147,6280854,6357992,6435706,6514095,6593228,6673106,6753649,6834722,6916183)
plot(Year, World.Population, xlab = "Years", ylab = "World Population (both sexes combined in thousands)", col="blue")
model=lm(World.Population~Year)
coef(model)
resid(model)
summary(model)
abline(model,col="red")
legend(1950,7e+06,c("Linear Model Fitting","World Population=(-146234895,78)+(76155,54)×Year","Adjusted R-
    squared:0,9954"), col=c("red"),text.col = "red", box.lty=0, bg="transparent")
****************************************************************************************************
Call:
lm(formula = World.Population ~ Year)
Residuals:
    Min      1Q  Median      3Q     Max
-105386  -94526    6192   53345  257375
Coefficients:
              Estimate Std. Error t value Pr(>|t|)
(Intercept) -1.462e+08  1.329e+06  -110.0   <2e-16 ***
Year         7.616e+04  6.713e+02   113.5   <2e-16 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1
Residual standard error: 92310 on 59 degrees of freedom
Multiple R-squared:  0.9954,      Adjusted R-squared:  0.9954
F-statistic: 1.287e+04 on 1 and 59 DF,  p-value: < 2.2e-16
******************************************************************************************
World Population=(-146234895,78)+(76155,54)×Year
******************************************************************************************
```

world population prediction X_1 & Year

```
******************************************************************************************
world population prediction X1
Year=c(2010,2015,2020,2025,2030,2035,2040,2045,2050,2055,2060,2065,2070,2075,2080,2085,2090,2095,2100)
World.Population.Prediction=c(6916183,7324782,7716749,8083413,8424937,8743447,9038687,9308438,9550945,9766475,
    9957399,10127007,10277339,10409149,10524161,10626467,10717401,10794252,10853849)
plot(Year, World.Population.Prediction, xlab = "Years", ylab = "World.Population.Prediction(both sexes combined in
    thousands)", pch=2, cex.main=1.5, col="forestgreen")
model=lm(World.Population.Prediction~Year)
coef(model)
resid(model)
summary(model)
abline(model,col="red")
legend(2007,1.1e+07,c("Linear Model Fitting","Population Prediction=(-78810091,40)+(42938,99)×Year","Adjusted R-
    squared:0.9385"), col=c("red"),text.col = "red", box.lty=0, bg="transparent")
******************************************************************************************
Call:
lm(formula = World.Population.Prediction ~ Year)
Residuals:
    Min      1Q  Median      3Q     Max
-581093 -212456   68881  260664  336944
Coefficients:
             Estimate Std. Error t value Pr(>|t|)
(Intercept) -78810091    5312691  -14.83 3.69e-11 ***
Year            42939       2585   16.61 6.07e-12 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1
```

```
Residual standard error: 308600 on 17 degrees of freedom
Multiple R-squared:  0.942,   Adjusted R-squared:  0.9385
F-statistic: 275.9 on 1 and 17 DF,  p-value: 6.073e-12
******************************************************************************************
World Population Prediction=(-78810091,40)+(42938,99)×Year
******************************************************************************************
Global Annual Temperature Anomalies X2 & Year
******************************************************************************************
global annual temperature anomalies X2
Year=c(1880,1881,1882,1883,1884,1885,1886,1887,1888,1889,1890,1891,1892,1893,1894,1895,1896,1897,1898,1899,1900
    ,1901,1902,1903,1904,1905,1906,1907,1908,1909,1910,1911,1912,1913,1914,1915,1916,1917,1918,1919,1920,192
    1,1922,1923,1924,1925,1926,1927,1928,1929,1930,1931,1932,1933,1934,1935,1936,1937,1938,1939,1940,1941,19
    42,1943,1944,1945,1946,1947,1948,1949,1950,1951,1952,1953,1954,1955,1956,1957,1958,1959,1960,1961,1962,1
    963,1964,1965,1966,1967,1968,1969,1970,1971,1972,1973,1974,1975,1976,1977,1978,1979,1980,1981,1982,1983,
    1984,1985,1986,1987,1988,1989,1990,1991,1992,1993,1994,1995,1996,1997,1998,1999,2000,2001,2002,2003,2004
    ,2005,2006,2007,2008,2009,2010,2011,2012,2013,2014)
Global.Annual.Temperature.Anomalies=c(-0.22,-0.14,-0.17,-0.2,-0.28,-0.26,-0.25,-0.31,-0.2,-0.11,-0.34,-0.27,-0.31,-0.36,-
    0.32,-0.25,-0.17,-0.18,-0.3,-0.19,-0.13,-0.19,-0.29,-0.36,-0.43,-0.29,-0.26,-0.41,-0.42,-0.47,-0.45,-0.44,-0.4,-0.38,-
    0.22,-0.16,-0.36,-0.44,-0.31,-0.29,-0.27,-0.21,-0.29,-0.25,-0.24,-0.21,-0.08,-0.18,-0.16,-0.31,-0.11,-0.08,-0.11,-0.25,-
    0.09,-0.15,-0.1,0.03,0.05,0.01,0.06,0.07,0.05,0.05,0.13,0,-0.08,-0.05,-0.11,-0.12,-0.19,-0.07,0.01,0.08,-0.12,-0.13,-
    0.18,0.03,0.05,0.03,-0.04,0.06,0.04,0.08,-0.19,-0.1,-0.04,-0.01,-0.05,0.06,0.04,-0.07,0.02,0.16,-0.07,-0.01,-
    0.12,0.15,0.06,0.12,0.23,0.28,0.09,0.27,0.12,0.08,0.15,0.29,0.36,0.24,0.39,0.38,0.19,0.21,0.29,0.43,0.33,0.46,0.62,0.
    41,0.41,0.53,0.62,0.6,0.52,0.66,0.6,0.63,0.49,0.6,0.67,0.55,0.58,0.6,0.68)
plot(Year, Global.Annual.Temperature.Anomalies, xlab = "Years", ylab = "Global Annual Temperature Anomalies (degrees
    Celsius)", col="blue")
model=lm(Global.Annual.Temperature.Anomalies~Year)
coef(model)
resid(model)
summary(model)
abline(model,col="red")
legend(1875,0.6,c("Linear Model Fitting","Global Annual Temperature Anomalies=(-13.025855461)+(
    0.006688811)×Year","Adjusted R-squared:0,7677"), col=c("red"),text.col = "red", box.lty=0, bg="transparent")
******************************************************************************************
Call:
lm(formula = Global.Annual.Temperature.Anomalies ~ Year)
Residuals:
     Min        1Q    Median        3Q       Max
-0.311235 -0.113616 -0.006329  0.108438  0.304202
Coefficients:
             Estimate Std. Error t value Pr(>|t|)
(Intercept) -1.303e+01  6.183e-01  -21.07   <2e-16 ***
Year         6.689e-03  3.175e-04   21.07   <2e-16 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1
Residual standard error: 0.1438 on 133 degrees of freedom
Multiple R-squared:  0.7694,          Adjusted R-squared:  0.7677
F-statistic: 443.8 on 1 and 133 DF,  p-value: < 2.2e-16
******************************************************************************************
Global Annual Temperature Anomalies=(-13.025855461)+( 0.006688811)×Year
******************************************************************************************
Global Annual Temperature Anomalies Projection X2 & Year
******************************************************************************************
global annual temperature anomalies projection X2
Year=c(2010,2020,2030,2040,2050,2060,2070,2080,2090,2100)
RCP2.6=c(0.62,1.07,1.24,1.50,1.65,1.71,1.71,1.79,1.79,1.79)
RCP4.5=c(0.59,0.83,1.22,1.57,1.97,2.19,2.32,2.54,2.59,2.64)
RCP6.0=c(0.64,0.90,1.17,1.41,1.81,2.18,2.52,2.88,3.24,3.60)
RCP8.5=c(0.62,0.99,1.39,1.77,2.37,2.99,3.61,4.22,4.81,5.40)
SRES.A1B=c(0.62,0.91,1.38,1.79,2.14,2.67,3.12,3.47,3.84,4.21)
Temperature.Change=data.frame(RCP2.6, RCP4.5, RCP6.0, RCP8.5, SRES.A1B)
plot(Year, RCP8.5, xlab="Years", ylab="Approximated global mean surface temperature change (°C)", pch=1,
    col="darkgreen")
points(Year, RCP2.6, pch=1, col="1")
points(Year, RCP4.5, pch=3, col="3")
points(Year, RCP6.0, pch=4, col="4")
points(Year, SRES.A1B, pch=6, col="6")
model1=lm(RCP2.6~Year)
```

```
coef(model1)
resid(model1)
summary(model1)
abline(model1,col="red")
model2=lm(RCP4.5~Year)
coef(model2)
resid(model2)
summary(model2)
abline(model2,col="red")
model3=lm(RCP6.0~Year)
coef(model3)
resid(model3)
summary(model3)
abline(model3,col="red")
model4=lm(RCP8.5~Year)
coef(model4)
resid(model4)
summary(model4)
abline(model4,col="red")
model5=lm(SRES.A1B~Year)
coef(model5)
resid(model5)
summary(model5)
abline(model5,col="red")
legend(2010,3,c("RCP2.6","RCP4.5","RCP6.0","RCP8.5","SRES.A1B"),col=c(1,2,3,4,5),pch=c(1,2,3,4,5), box.lty=0,
        bg="transparent")
legend(2008,5.5,c("Linear Model Fitting","RCP2.6=(-22.18909091)+(0.01152121)×Year", "RCP4.5=(-
        47.77290909)+(0.02414545)×Year","RCP6.0=(-66.80127273)+(0.03349697)×Year","RCP8.5=(-
        109.33618182)+(0.05457576)×Year","SRES.A1B=(-82.01436364)+(0.04108485)×Year"), col=c("red"),text.col =
        "red", box.lty=0, bg="transparent")
****************************************************************************************
Call:
lm(formula = RCP2.6 ~ Year)
Residuals:
    Min       1Q   Median       3Q      Max
-0.34855 -0.07862  0.02800  0.13659  0.22061
Coefficients:
            Estimate Std. Error t value Pr(>|t|)
(Intercept) -22.189091   4.331159  -5.123 0.000904 ***
Year          0.011521   0.002107   5.467 0.000597 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
Residual standard error: 0.1914 on 8 degrees of freedom
Multiple R-squared:  0.7889, Adjusted R-squared:  0.7625
F-statistic: 29.89 on 1 and 8 DF,  p-value: 0.0005966
Call:
lm(formula = RCP4.5 ~ Year)
Residuals:
    Min       1Q   Median       3Q      Max
-0.29254 -0.15236  0.03191  0.10645  0.24473
Coefficients:
            Estimate Std. Error t value Pr(>|t|)
(Intercept) -47.772909   4.323370  -11.05 4.01e-06 ***
Year          0.024145   0.002104   11.48 3.01e-06 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
Residual standard error: 0.1911 on 8 degrees of freedom
Multiple R-squared:  0.9428, Adjusted R-squared:  0.9356
F-statistic: 131.7 on 1 and 8 DF,  p-value: 3.007e-06
Call:
lm(formula = RCP6.0 ~ Year)
Residuals:
     Min        1Q    Median        3Q       Max
-0.122545 -0.026303 -0.004939  0.036197  0.112364
Coefficients:
            Estimate Std. Error t value Pr(>|t|)
(Intercept) -6.680e+01  1.567e+00  -42.63 1.01e-10 ***
```

```
Year        3.350e-02  7.624e-04   43.94 7.95e-11 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
Residual standard error: 0.06925 on 8 degrees of freedom
Multiple R-squared:  0.9959, Adjusted R-squared:  0.9954
F-statistic:  1930 on 1 and 8 DF,  p-value: 7.946e-11
Call:
lm(formula = RCP8.5 ~ Year)
Residuals:
     Min       1Q   Median       3Q      Max
-0.228364 -0.090561  0.006485  0.083076  0.258909
Coefficients:
            Estimate Std. Error t value Pr(>|t|)
(Intercept) -1.093e+02  3.537e+00  -30.91 1.30e-09 ***
Year        5.458e-02  1.721e-03   31.71 1.06e-09 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
Residual standard error: 0.1563 on 8 degrees of freedom
Multiple R-squared:  0.9921, Adjusted R-squared:  0.9911
F-statistic:  1006 on 1 and 8 DF,  p-value: 1.064e-09
Call:
lm(formula = SRES.A1B ~ Year)
Residuals:
     Min       1Q   Median       3Q      Max
-0.069576 -0.043606 -0.008303  0.044152  0.088727
Coefficients:
            Estimate Std. Error t value Pr(>|t|)
(Intercept) -8.201e+01  1.303e+00  -62.93 4.52e-12 ***
Year        4.108e-02  6.341e-04   64.79 3.58e-12 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
Residual standard error: 0.0576 on 8 degrees of freedom
Multiple R-squared:  0.9981, Adjusted R-squared:  0.9979
F-statistic:  4198 on 1 and 8 DF,  p-value: 3.583e-12
*************************************************************************************
Global Annual Temperature Anomalies Projection RCP2.6=(-22.18909091)+(0.01152121)×Year Adjusted R-squared:
    0.7625
Global Annual Temperature Anomalies Projection RCP4.5=(-47.77290909)+(0.02414545)×Year Adjusted R-squared:
    0.9356
Global Annual Temperature Anomalies Projection RCP6.0=(-66.80127273)+(0.03349697)×Year Adjusted R-squared:
    0.9954
Global Annual Temperature Anomalies Projection RCP8.5=(-109.33618182)+(0.05457576)×Year Adjusted R-squared:
    0.9911
Global Annual Temperature Anomalies Projection SRES.A1B=(-82.01436364)+(0.04108485)×Year Adjusted R-squared:
    0.9979
*************************************************************************************
world power installed capacity Y & Year
*************************************************************************************
world power installed capacity Y
Year=c(1980,1981,1982,1983,1984,1985,1986,1987,1988,1989,1990,1991,1992,1993,1994,1995,1996,1997,1998,1999,2000
    ,2001,2002,2003,2004,2005,2006,2007,2008,2009,2010,2011,2012)
World.Power.Installed.Capacity.GW=c(1983,2071,2147,2217,2313,2399,2471,2542,2611,2702,2754,2797,2858,2928,3000,3
    055,3135,3202,3258,3338,3457,3560,3697,3846,3983,4123,4303,4478,4650,4852,5081,5314,5549)
Conversion=c(0.6)
World.Peak.Power.Demand.GW= World.Power.Installed.Capacity.GW* Conversion
plot(Year, World.Peak.Power.Demand.GW, xlab = "Years", ylab = "Annual Global Peak Power Demand (GW)", col="blue")
model=lm(World.Peak.Power.Demand.GW~Year)
coef(model)
resid(model)
summary(model)
abline(model,col="red")
legend(1980,3250,c("Linear Model Fitting","Annual Global Peak Power Demand (GW)=( -
    116963.22139)+(59.60695)×Year","Adjusted R-squared: 0.9444"), col=c("red"),text.col = "red", box.lty=0,
    bg="transparent")
*************************************************************************************
Call:
lm(formula = World.Peak.Power.Demand.GW ~ Year)
```

```
Residuals:
   Min      1Q  Median      3Q     Max
-188.28 -119.65   -2.21   90.83  363.43
Coefficients:
              Estimate Std. Error t value Pr(>|t|)
(Intercept) -1.170e+05  5.098e+03  -22.95   <2e-16 ***
Year         5.961e+01  2.554e+00   23.34   <2e-16 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
Residual standard error: 139.7 on 31 degrees of freedom
Multiple R-squared:  0.9462,	Adjusted R-squared:  0.9444
F-statistic: 544.7 on 1 and 31 DF,  p-value: < 2.2e-16
*****************************************************************************************
Annual Global Peak Power Demand (GW)=( -116963.22139)+(59.60695)×Year
*****************************************************************************************
world population historical X1 & annual peak power load Y
*****************************************************************************************
world population historical X1 & annual peak power load Y
Year=c(1980,1981,1982,1983,1984,1985,1986,1987,1988,1989,1990,1991,1992,1993,1994,1995,1996,1997,1998,1999,2000
      ,2001,2002,2003,2004,2005,2006,2007,2008,2009,2010)
World.Population=c(4449049,4528235,4608962,4691560,4776393,4863602,4953377,5045316,5138215,5230452,5320817,5
      408909,5494900,5578865,5661086,5741822,5821017,5898688,5975304,6051478,6127700,6204147,6280854,63579
      92,6435706,6514095,6593228,6673106,6753649,6834722,6916183)
World.Electricity.Installed.Capacity.GW=c(1983,2071,2147,2217,2313,2399,2471,2542,2611,2702,2754,2797,2858,2928,30
      00,3055,3135,3202,3258,3338,3457,3560,3697,3846,3983,4123,4303,4478,4650,4852,5081)
Conversion=c(0.6)
World.Peak.Power.Demand.GW= World.Electricity.Installed.Capacity.GW* Conversion
plot(World.Population, World.Peak.Power.Demand.GW, xlab = "World Population (both sexes combined in thousands)",
      ylab = "Annual Global Peak Power Demand (GW)")
model=lm(World.Peak.Power.Demand.GW~ World.Population)
coef(model)
resid(model)
summary(model)
abline(model,col="red")
legend(4300000,3000,c("Linear Model Fitting","Annual Global Peak Power Demand (GW)=( -1.883384e+03)+(6.684671e-
      04)×World Population","Adjusted R-squared:0.9461"), col=c("red"),text.col = "red", box.lty=0, bg="transparent")
*****************************************************************************************
Call:
lm(formula = World.Peak.Power.Demand.GW ~ World.Population)
Residuals:
    Min       1Q   Median       3Q      Max
-159.030  -98.913    2.726   77.876  308.743
Coefficients:
                  Estimate Std. Error t value Pr(>|t|)
(Intercept)      -1.883e+03  1.675e+02  -11.24 4.34e-12 ***
World.Population  6.685e-04  2.911e-05   22.96  < 2e-16 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
Residual standard error: 119.3 on 29 degrees of freedom
Multiple R-squared:  0.9479,	Adjusted R-squared:  0.9461
F-statistic: 527.3 on 1 and 29 DF,  p-value: < 2.2e-16
*****************************************************************************************
Annual Global Peak Power Demand (GW)=(-1.883384e+03)+(6.684671e-04)×World Population
*****************************************************************************************
global annual temperature anomalies X2 & annual peak power load Y
*****************************************************************************************
global annual temperature anomalies X2 & annual peak power load Y
Year=c(1980,1981,1982,1983,1984,1985,1986,1987,1988,1989,1990,1991,1992,1993,1994,1995,1996,1997,1998,1999,2000
      ,2001,2002,2003,2004,2005,2006,2007,2008,2009,2010)
Global.Annual.Temperature.Anomalies=c(0.23,0.28,0.09,0.27,0.12,0.08,0.15,0.29,0.36,0.24,0.39,0.38,0.19,0.21,0.29,0.43,0.
      33,0.46,0.62,0.41,0.41,0.53,0.62,0.6,0.52,0.66,0.6,0.63,0.49,0.6,0.67)
World.Electricity.Installed.Capacity.GW=c(1983,2071,2147,2217,2313,2399,2471,2542,2611,2702,2754,2797,2858,2928,30
      00,3055,3135,3202,3258,3338,3457,3560,3697,3846,3983,4123,4303,4478,4650,4852,5081)
Conversion=c(0.6)
World.Peak.Power.Demand.GW= World.Electricity.Installed.Capacity.GW* Conversion
plot(Global.Annual.Temperature.Anomalies, World.Peak.Power.Demand.GW, xlab = "Global Annual Temperature
      Anomalies (degrees Celsius)", ylab = "Annual Global Peak Power Demand (GW)")
```

```
model=lm(World.Peak.Power.Demand.GW~ Global.Annual.Temperature.Anomalies)
coef(model)
resid(model)
summary(model)
abline(model,col="red")
legend(0.05,3000,c("Linear Model Fitting"," Annual Global Peak Power Demand (GW)=(994.469)+(2391.610)×Global
    Annual Temperature Anomalies","Adjusted R-squared:0.7046"), col=c("red"),text.col = "red", box.lty=0,
    bg="transparent")
******************************************************************************************
Call:
lm(formula = World.Peak.Power.Demand.GW ~ Global.Annual.Temperature.Anomalies)
Residuals:
   Min      1Q  Median      3Q     Max
-522.47 -207.47   52.74  152.03  623.64
Coefficients:
                                    Estimate Std. Error t value Pr(>|t|)
(Intercept)                            994.5      120.9   8.224 4.56e-09 ***
Global.Annual.Temperature.Anomalies   2391.6      280.8   8.518 2.20e-09 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1
Residual standard error: 279.2 on 29 degrees of freedom
Multiple R-squared:  0.7145,	Adjusted R-squared:  0.7046
F-statistic: 72.56 on 1 and 29 DF,  p-value: 2.197e-09
******************************************************************************************
```

Annual Global Peak Power Demand (GW)=(994.469)+(2391.610)×Global Annual Temperature Anomalies

****

world population historical X_1 & global annual temperature anomalies X_2

****

world population historical X_1 & global annual temperature anomalies X_2

```
Year=c(1980,1981,1982,1983,1984,1985,1986,1987,1988,1989,1990,1991,1992,1993,1994,1995,1996,1997,1998,1999,2000
    ,2001,2002,2003,2004,2005,2006,2007,2008,2009,2010)
World.Population=c(4449049,4528235,4608962,4691560,4776393,4863602,4953377,5045316,5138215,5230452,5320817,5
    408909,5494900,5578865,5661086,5741822,5821017,5898688,5975304,6051478,6127700,6204147,6280854,63579
    92,6435706,6514095,6593228,6673106,6753649,6834722,6916183)
Global.Annual.Temperature.Anomalies=c(0.23,0.28,0.09,0.27,0.12,0.08,0.15,0.29,0.36,0.24,0.39,0.38,0.19,0.21,0.29,0.43,0.
    33,0.46,0.62,0.41,0.41,0.53,0.62,0.6,0.52,0.66,0.6,0.63,0.49,0.6,0.67)
plot(World.Population, Global.Annual.Temperature.Anomalies, xlab = "World Population (both sexes combined in
    thousands)", ylab = "Global Annual Temperature Anomalies (degrees Celsius)")
model=lm(Global.Annual.Temperature.Anomalies~World.Population)
coef(model)
resid(model)
summary(model)
abline(model,col="red")
legend(4500000,0.65,c("Linear Model Fitting","Global Annual Temperature Anomalies=(-8.103186e-01)+(2.106483e-
    07)×World Population","Adjusted R-squared:0.745"), col=c("red"),text.col = "red", box.lty=0, bg="transparent")
******************************************************************************************
Call:
lm(formula = Global.Annual.Temperature.Anomalies ~ World.Population)
Residuals:
     Min       1Q   Median       3Q      Max
-0.15717 -0.07319  0.02344  0.07526  0.17163
Coefficients:
                  Estimate Std. Error t value Pr(>|t|)
(Intercept)     -8.103e-01  1.287e-01  -6.294 7.12e-07 ***
World.Population  2.106e-07  2.237e-08   9.416 2.54e-10 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1
Residual standard error: 0.09167 on 29 degrees of freedom
Multiple R-squared:  0.7535, Adjusted R-squared:  0.745
F-statistic: 88.67 on 1 and 29 DF,  p-value: 2.536e-10
******************************************************************************************
```

Global Annual Temperature Anomalies=(-8.103186e-01)+(2.106483e-07)×World Population

****

linear multivariable regression model for the variables X_1, X_2, and Y

****

linear multivariable regression model for the variables X_1, X_2, and Y

```
Year=c(1980,1981,1982,1983,1984,1985,1986,1987,1988,1989,1990,1991,1992,1993,1994,1995,1996,1997,1998,1999,2000
,2001,2002,2003,2004,2005,2006,2007,2008,2009,2010)
World.Population=c(4449049,4528235,4608962,4691560,4776393,4863602,4953377,5045316,5138215,5230452,5320817,5
408909,5494900,5578865,5661086,5741822,5821017,5898688,5975304,6051478,6127700,6204147,6280854,63579
92,6435706,6514095,6593228,6673106,6753649,6834722,6916183)
Global.Annual.Temperature.Anomalies=c(0.23,0.28,0.09,0.27,0.12,0.08,0.15,0.29,0.36,0.24,0.39,0.38,0.19,0.21,0.29,0.43,0.
33,0.46,0.62,0.41,0.41,0.53,0.62,0.6,0.52,0.66,0.6,0.63,0.49,0.6,0.67)
World.Electricity.Installed.Capacity.GW=c(1983,2071,2147,2217,2313,2399,2471,2542,2611,2702,2754,2797,2858,2928,30
00,3055,3135,3202,3258,3338,3457,3560,3697,3846,3983,4123,4303,4478,4650,4852,5081)
Conversion=c(0.6)
World.Peak.Power.Demand.GW= World.Electricity.Installed.Capacity.GW* Conversion
model=lm(formula=World.Peak.Power.Demand.GW~World.Population+Global.Annual.Temperature.Anomalies)
summary(model)
coef(model)
resid(model)
layout(matrix(1:4,2,2))
plot(model)
****************************************************************************************
lm(formula = World.Peak.Power.Demand.GW ~ World.Population +
   Global.Annual.Temperature.Anomalies)
Residuals:
     Min       1Q   Median       3Q      Max
-158.957  -98.923    2.594   77.865  308.712
Coefficients:
                                     Estimate Std. Error t value Pr(>|t|)
(Intercept)                        -1.882e+03  2.623e+02  -7.177 8.22e-08 ***
World.Population                    6.682e-04  5.968e-05  11.197 7.50e-12 ***
Global.Annual.Temperature.Anomalies  1.345e+00  2.459e+02   0.005    0.996
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
Residual standard error: 121.4 on 28 degrees of freedom
Multiple R-squared:  0.9479, Adjusted R-squared:  0.9441
F-statistic: 254.6 on 2 and 28 DF,  p-value: < 2.2e-16
****************************************************************************************
Annual Global Peak Power Demand (GW)=(-1.882294e+03)+(6.681837e-04)×World Population+(1.345441e+00)×Global
Annual Temperature Anomalies
****************************************************************************************
```

APPENDIX 2

Script for 5.4.1 Scilab Editor

```
//Experimental FIS for peak power demand forecasting of the Global Grid Scilab 5.4.1 SciFLT Model
//Create a new fls structure.
PPDGG=newfls();
//Add type, methods, parameters etc.
PPDGG.name="paper";
PPDGG.comment="Experimental FIS for peak power demand forecasting of Global Grid";
PPDGG.type="ts";
PPDGG.SNorm="asum";
PPDGG.TNorm="aprod";
PPDGG.Comp="one";
PPDGG.defuzzMethod="wtaver";
//Add a new variable (X1:world population) to the fls and return it
PPDGG=addvar(PPDGG,"input","world population",[4440000 10900000]);
//Add a new member function to the fls structure
PPDGG=addmf(PPDGG,"input",1,"very very low","trimf",[4440000 4440000 5517000]);
PPDGG=addmf(PPDGG,"input",1,"very low","trimf",[4440000 5517000 6594000]);
PPDGG=addmf(PPDGG,"input",1,"low","trimf",[5517000 6594000 7670000]);
PPDGG=addmf(PPDGG,"input",1,"moderate","trimf",[6594000 7670000 8747000]);
PPDGG=addmf(PPDGG,"input",1,"high","trimf",[7670000 8747000 9824000]);
PPDGG=addmf(PPDGG,"input",1,"very high","trimf",[8747000 9824000 10900000]);
PPDGG=addmf(PPDGG,"input",1,"very very high","trimf",[9824000 10900000 10900000]);
//Add a new variable (X2:global annual temperature anomalies) to the fls and return it
PPDGG=addvar(PPDGG,"input","global annual temperature anomalies",[0.00 6.00]);
//Add a new member function to the fls structure
PPDGG=addmf(PPDGG,"input",2,"almost the same","trimf",[0.0 0.0 1.0]);
PPDGG=addmf(PPDGG,"input",2,"fairly hotter","trimf",[0.0 1.0 2.0]);
PPDGG=addmf(PPDGG,"input",2,"rather hotter","trimf",[1.0 2.0 3.0]);
PPDGG=addmf(PPDGG,"input",2,"hotter","trimf",[2.0 3.0 4.0]);
PPDGG=addmf(PPDGG,"input",2,"very hotter","trimf",[3.0 4.0 5.0]);
PPDGG=addmf(PPDGG,"input",2,"very very hotter","trimf",[4.0 5.0 6.0]);
PPDGG=addmf(PPDGG,"input",2,"extremely hotter","trimf",[5.0 6.0 6.0]);
//Add a new variable (Y:annual peak power demand of Global Grid) to the fls and return it
PPDGG=addvar(PPDGG,"output","annual peak power demand of Global Grid (GW)",[1100 5500]);
//Add a new member function to the fls structure
PPDGG=addmf(PPDGG,"output",1,"very very low","constant", 1150.0);
PPDGG=addmf(PPDGG,"output",1,"very low","constant", 1850.0);
PPDGG=addmf(PPDGG,"output",1,"low","constant",2550.0);
PPDGG=addmf(PPDGG,"output",1,"moderate","constant",3300.0);
PPDGG=addmf(PPDGG,"output",1,"high","constant",4000.0);
PPDGG=addmf(PPDGG,"output",1,"very high","constant", 4700.0);
PPDGG=addmf(PPDGG,"output",1,"very very high","constant", 5450.0);
// Plot the fls input(s) or output(s) variable(s)
scf();clf();
plotvar(PPDGG,"input",[1 2]);
scf();clf();
plotvar(PPDGG,"output",1);
// Add 25 rules and display them in verbose format.
PPDGG=addrule(PPDGG,[1 1 1 1 1; 1 2 1 1 1; 1 3 2 1 1; 1 4 2 1 1; 1 5 3 1 1; 1 6 3 1 1; 1 7 4 1 1; 2 1 2 1 1; 2 2 2 1 1; 2 3 3 1
    1; 2 4 3 1 1; 2 5 4 1 1; 2 6 4 1 1; 2 7 5 1 1; 3 1 3 1 1; 3 2 3 1 1; 3 3 4 1 1; 3 4 4 1 1; 3 5 5 1 1; 3 6 5 1 1; 3 7 6 1 1; 4 1
    4 1 1; 4 2 4 1 1; 4 3 5 1 1; 4 4 4 1 1; 4 5 5 1 1; 4 6 5 1 1; 4 7 6 1 1; 5 1 5 1 1; 5 2 5 1 1; 5 3 5 1 1; 5 4 5 1 1; 5 5 5 1 1;
    5 6 5 1 1; 5 7 6 1 1; 6 1 5 1 1; 6 2 5 1 1; 6 3 5 1 1; 6 4 6 1 1; 6 5 6 1 1; 6 6 6 1 1; 6 7 7 1 1; 7 1 5 1 1; 7 2 6 1 1; 7 3 6 1
    1; 7 4 7 1 1; 7 5 7 1 1; 7 6 7 1 1; 7 7 7 1 1])
// Show the fls rules
printrule(PPDGG);
//Save the structure as PPDGGpaper.fls
savefls(PPDGG,"C:/PPDGGpaper");
//Plot the output as a function (the surface view: 3D) of the two inputs.
scf();clf();
plotsurf(PPDGG,[1 2],[1],[0 0],[50 50],2);
//Get experimental FIS for electricity demand forecasting of Global Grid Scilab 5.4.1 SciFLT Model from PPDGGpaper.fls
PPDGG=loadfls("C:/PPDGGpaper");
//Forecast electricity demand of Global Grid (from 2011 to 2100 with the intervals of 10 years)
RCP85PP1=evalfls([6916183 0.62],PPDGG), RCP85PP2=evalfls([7716749 0.99],PPDGG), RCP85PP3=evalfls([8424937
    1.39],PPDGG), RCP85PP4=evalfls([9038687 1.77],PPDGG), RCP85PP5=evalfls([9550945 2.37],PPDGG),
```

RCP85PP6=evalfls([9957399 2.99],PPDGG), RCP85PP7=evalfls([10277339 3.61],PPDGG),
RCP85PP8=evalfls([10524161 4.22],PPDGG), RCP85PP9=evalfls([10717401 4.81],PPDGG),
RCP85PP10=evalfls([10853849 5.40],PPDGG)
RCP85PP1=2774.5699 RCP85PP2=3330.3847 RCP85PP3=3872.3111 RCP85PP4=4000. RCP85PP5=4193.335
RCP85PP6=4785.9206 RCP85PP7=5015.9891 RCP85PP8=5188.0304 RCP85PP9=5322.7237 PP10=5430.6989
//Similar For All RCP2.6, RCP4.5, RCP6.0, RCP8.5, SRES A1B
Note: Script for Fuzzy Toolbox 0.4.6 is tested on Scilab 5.5.2 on 25th August 2015. Please run the *.fls file or the script on Fuzzy Toolbox 0.4.6 Scilab 5.5.2.
****

APPENDIX 3

Rule base

R1: IF (world population IS very very low) AND (global annual temperature anomalies IS almost the same) THEN (annual peak power demand of Global Grid (GW) IS very very low) weigth=1
R2: IF (world population IS very very low) AND (global annual temperature anomalies IS fairly hotter) THEN (annual peak power demand of Global Grid (GW) IS very very low) weigth=1
R3: IF (world population IS very very low) AND (global annual temperature anomalies IS rather hotter) THEN (annual peak power demand of Global Grid (GW) IS very low) weigth=1
R4: IF (world population IS very very low) AND (global annual temperature anomalies IS hotter) THEN (annual peak power demand of Global Grid (GW) IS very low) weigth=1
R5: IF (world population IS very very low) AND (global annual temperature anomalies IS very hotter) THEN (annual peak power demand of Global Grid (GW) IS low) weigth=1
R6: IF (world population IS very very low) AND (global annual temperature anomalies IS very very hotter) THEN (annual peak power demand of Global Grid (GW) IS low) weigth=1
R7: IF (world population IS very very low) AND (global annual temperature anomalies IS extremely hotter) THEN (annual peak power demand of Global Grid (GW) IS moderate) weigth=1
R8: IF (world population IS very low) AND (global annual temperature anomalies IS almost the same) THEN (annual peak power demand of Global Grid (GW) IS very low) weigth=1
R9: IF (world population IS very low) AND (global annual temperature anomalies IS fairly hotter) THEN (annual peak power demand of Global Grid (GW) IS very low) weigth=1
R10: IF (world population IS very low) AND (global annual temperature anomalies IS rather hotter) THEN (annual peak power demand of Global Grid (GW) IS low) weigth=1
R11: IF (world population IS very low) AND (global annual temperature anomalies IS hotter) THEN (annual peak power demand of Global Grid (GW) IS low) weigth=1
R12: IF (world population IS very low) AND (global annual temperature anomalies IS very hotter) THEN (annual peak power demand of Global Grid (GW) IS moderate) weigth=1
R13: IF (world population IS very low) AND (global annual temperature anomalies IS very very hotter) THEN (annual peak power demand of Global Grid (GW) IS moderate) weigth=1
R14: IF (world population IS very low) AND (global annual temperature anomalies IS extremely hotter) THEN (annual peak power demand of Global Grid (GW) IS high) weigth=1
R15: IF (world population IS low) AND (global annual temperature anomalies IS almost the same) THEN (annual peak power demand of Global Grid (GW) IS low) weigth=1
R16: IF (world population IS low) AND (global annual temperature anomalies IS fairly hotter) THEN (annual peak power demand of Global Grid (GW) IS low) weigth=1
R17: IF (world population IS low) AND (global annual temperature anomalies IS rather hotter) THEN (annual peak power demand of Global Grid (GW) IS moderate) weigth=1
R18: IF (world population IS low) AND (global annual temperature anomalies IS hotter) THEN (annual peak power demand of Global Grid (GW) IS moderate) weigth=1
R19: IF (world population IS low) AND (global annual temperature anomalies IS very hotter) THEN (annual peak power demand of Global Grid (GW) IS high) weigth=1
R20: IF (world population IS low) AND (global annual temperature anomalies IS very very hotter) THEN (annual peak power demand of Global Grid (GW) IS high) weigth=1
R21: IF (world population IS low) AND (global annual temperature anomalies IS extremely hotter) THEN (annual peak power demand of Global Grid (GW) IS very high) weigth=1
R22: IF (world population IS moderate) AND (global annual temperature anomalies IS almost the same) THEN (annual peak power demand of Global Grid (GW) IS moderate) weigth=1
R23: IF (world population IS moderate) AND (global annual temperature anomalies IS fairly hotter) THEN (annual peak power demand of Global Grid (GW) IS moderate) weigth=1
R24: IF (world population IS moderate) AND (global annual temperature anomalies IS rather hotter) THEN (annual peak power demand of Global Grid (GW) IS high) weigth=1
R25: IF (world population IS moderate) AND (global annual temperature anomalies IS hotter) THEN (annual peak power demand of Global Grid (GW) IS moderate) weigth=1
R26: IF (world population IS moderate) AND (global annual temperature anomalies IS very hotter) THEN (annual peak power demand of Global Grid (GW) IS high) weigth=1
R27: IF (world population IS moderate) AND (global annual temperature anomalies IS very very hotter) THEN (annual peak power demand of Global Grid (GW) IS high) weigth=1
R28: IF (world population IS moderate) AND (global annual temperature anomalies IS extremely hotter) THEN (annual peak power demand of Global Grid (GW) IS very high) weigth=1
R29: IF (world population IS high) AND (global annual temperature anomalies IS almost the same) THEN (annual peak power demand of Global Grid (GW) IS high) weigth=1
R30: IF (world population IS high) AND (global annual temperature anomalies IS fairly hotter) THEN (annual peak power demand of Global Grid (GW) IS high) weigth=1
R31: IF (world population IS high) AND (global annual temperature anomalies IS rather hotter) THEN (annual peak power demand of Global Grid (GW) IS high) weigth=1
R32: IF (world population IS high) AND (global annual temperature anomalies IS hotter) THEN (annual peak power demand of Global Grid (GW) IS high) weigth=1

R33: IF (world population IS high) AND (global annual temperature anomalies IS very hotter) THEN (annual peak power demand of Global Grid (GW) IS high) weigth=1
R34: IF (world population IS high) AND (global annual temperature anomalies IS very very hotter) THEN (annual peak power demand of Global Grid (GW) IS high) weigth=1
R35: IF (world population IS high) AND (global annual temperature anomalies IS extremely hotter) THEN (annual peak power demand of Global Grid (GW) IS very high) weigth=1
R36: IF (world population IS very high) AND (global annual temperature anomalies IS almost the same) THEN (annual peak power demand of Global Grid (GW) IS high) weigth=1
R37: IF (world population IS very high) AND (global annual temperature anomalies IS fairly hotter) THEN (annual peak power demand of Global Grid (GW) IS high) weigth=1
R38: IF (world population IS very high) AND (global annual temperature anomalies IS rather hotter) THEN (annual peak power demand of Global Grid (GW) IS high) weigth=1
R39: IF (world population IS very high) AND (global annual temperature anomalies IS hotter) THEN (annual peak power demand of Global Grid (GW) IS very high) weigth=1
R40: IF (world population IS very high) AND (global annual temperature anomalies IS very hotter) THEN (annual peak power demand of Global Grid (GW) IS very high) weigth=1
R41: IF (world population IS very high) AND (global annual temperature anomalies IS very very hotter) THEN (annual peak power demand of Global Grid (GW) IS very high) weigth=1
R42: IF (world population IS very high) AND (global annual temperature anomalies IS extremely hotter) THEN (annual peak power demand of Global Grid (GW) IS very very high) weigth=1
R43: IF (world population IS very very high) AND (global annual temperature anomalies IS almost the same) THEN (annual peak power demand of Global Grid (GW) IS high) weigth=1
R44: IF (world population IS very very high) AND (global annual temperature anomalies IS fairly hotter) THEN (annual peak power demand of Global Grid (GW) IS very high) weigth=1
R45: IF (world population IS very very high) AND (global annual temperature anomalies IS rather hotter) THEN (annual peak power demand of Global Grid (GW) IS very high) weigth=1
R46: IF (world population IS very very high) AND (global annual temperature anomalies IS hotter) THEN (annual peak power demand of Global Grid (GW) IS very very high) weigth=1
R47: IF (world population IS very very high) AND (global annual temperature anomalies IS very hotter) THEN (annual peak power demand of Global Grid (GW) IS very very high) weigth=1
R48: IF (world population IS very very high) AND (global annual temperature anomalies IS very very hotter) THEN (annual peak power demand of Global Grid (GW) IS very very high) weigth=1
R49: IF (world population IS very very high) AND (global annual temperature anomalies IS extremely hotter) THEN (annual peak power demand of Global Grid (GW) IS very very high) weigth=1
****

APPENDIX 4

R Scripts of Figure 7
Projection Y & Year
****

```
Year=c(2010,2020,2030,2040,2050,2060,2070,2080,2090,2100)
World.Peak.Power.Demand.GW.RCP2.6=c(2774.5699,3377.2578 ,3840.9122 ,4000. ,4000.
    ,4086.7837,4294.9231,4455.4951,4581.2088,4669.9761)
 World.Peak.Power.Demand.GW.RCP4.5=c(2774.5699,3330.3847,3836.7257,4000.
    ,4000.,4220.9615,4525.6642,4851.0642,5018.7026 ,5148.6036)
World.Peak.Power.Demand.GW.RCP6.0=c(2774.5699,3330.3847,3826.2594,4000.,4000.,4213.8995,4669.8774
    ,5100.1262,5322.7237,5417.8316)
World.Peak.Power.Demand.GW.RCP8.5=c(2774.5699,3330.3847,3872.3111,4000.,4193.335,4785.9206,5015.9891,5188.03
    04,5322.7237,5430.6989)
World.Peak.Power.Demand.GW.SRES.A1B=c(2774.5699,3330.3847,3870.2179,4000.,4073.1538,
    4559.937,5015.9891,5188.0304,5322.7237,5417.8316)
plot(Year, World.Peak.Power.Demand.GW.RCP8.5, xlab="Years", ylab="Predicted World Peak Power Demand (GW)",
    pch=2, type="b", col="2")
points(Year, World.Peak.Power.Demand.GW.RCP2.6, pch=1, type="b", col="1")
points(Year, World.Peak.Power.Demand.GW.RCP4.5, pch=3, type="b", col="3")
points(Year, World.Peak.Power.Demand.GW.RCP6.0, pch=4, type="b", col="4")
points(Year, World.Peak.Power.Demand.GW.SRES.A1B, pch=6, type="b", col="6")
legend(2010,5500,c("Peak Power of RCP2.6","Peak Power of RCP4.5"," Peak Power of RCP6.0"," Peak Power of RCP8.5","
  Peak Power of SRES.A1B"),col=c(1,2,3,4,5),pch=c(1,2,3,4,5))
```