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A Europe-South America Network for Climate Change Assessment

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SEVENTH FRAMEWORK PROGRAMME

**Deliverables**

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**CLARIS LPB**
**A Europe-South America Network for Climate Change Assessment and Impact Studies in La Plata Basin**

**DELIVERABLES**

# D9.17: Monthly rainfall-runoff model for South/South-East Brazil validated

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| D9.17 | Monthly rainfall-runoff model for South/South-East Brazil validated | WP9 | P12-UFPR | 21,71 | O | CO | 36 |

# Deliverable 9.17:
# Monthly rainfall-runoff model for South/South-East Brazil validated

**OBJECTIVE** - Identification of the best ANN model to transform rainfall scenarios into runoff in the nine river basins studied. Computer programs necessary for implementing the natural energy hydrograph method to determine the firm energy of the Brazilian South-Southeast system to various climate change scenarios. For each task a computer program has been developed: ANN rainfall-runoff model; Aggregation model; Statistical parameter model; Synthetic series generation model; System simulation model.

**Keywords**: Artificial neural network, rainfall-runoff model, computer programs

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Contents

**ABSRACT—**This report presents the results of identification of the best ANN model to transform rainfall scenarios into runoff in the river basins (Task D9.17) and the general aspects of the natural energy hydrograph method. Computing routines development is presented here (Task D9.18). The natural energy hydrograph method transforms the natural inflows to the power plants at their present location into natural energy input. The accumulated energy input to a system is then called the system natural energy input. Furthermore, the active storages of the reservoirs of a system can also be transformed into a single equivalent reservoir by means of aggregation. With the natural energy series available, it is possible to generate synthetic energy series. The firm energies for several hydrologic scenarios are derived using the synthetic energy series. This procedure is then applied to the investigation of the resulting effect of the climate changes over the interconnected hydropower plant system.

## 1. Rainfall- runoff models for river-basins – TASK D9.17

The problem of training an ANN to solve a rainfall-runoff type problem is to fit a suitable function to a data sample. The rainfall-runoff process is non-linear, and the functional form for the fit is unknown. In this case, applying an ANN not only means to fit the best weights and biases to the sample of data observed, but also to investigate, by varying the ANN architecture, which is the best functional form for to observed data.

The ANNs used are of the three-layer MLP type. The input layer does not have transfer functions. All neurons of the middle layer and the output layer have a transfer function of the sigmoid and linear type, respectively.

In order to investigate the best functional form, 24 ANNs were created with variations in the number of inputs and the number of neurons in the middle layers. The output is always runoff. Each combination of inputs was called a model. Table 01 shows the input and output for each of these models. For each model 3, 5, 8 and 10 neurons were used in the middle layer, making up the total of 24 ANNs combinations. Varying both the number of neurons in the middle layer and the number of inputs, allows the evaluation of ANN sensitivity in terms of its architecture.

During the training of the 24 ANNs, the following parameters were considered: length of data series, number of iterations called epochs and initialization of weights. Before the training, all inputs were normalized between 0.1 and 0.9 according to Sajikumar & Thandaveswara (1999).

All the ANNs were trained with three different sets of data. From the 221 months available, sets of 60, 120 and 180 items were used for training, and 161,101 and 41 items for validation, respectively. These lengths of the data series were chosen according to Lima & Ferreira Filho (2003).

The combination, during the training, of the ANN architecture, the input sets, the number of initializations and the number of iterations generated a total of 1296 results for analysis. In order to evaluate the influence of all elements proposed in the ANN training, an algorithm was created in MATLAB software, that manipulates the data, trains, simulates, computes the statistics of the results and stores all responses in an output file. The statistics used were the correlation coefficient and the percentage difference of the volumes.

**TABLE 01 - MODELS PROPOSED.**

| MODEL | INPUTS | OUTPUTS |
|---|---|---|
| 1 | *P (t) EVT (t)* | *Q (t)* |
| 2 | *P(t) EVT(t) Q (t-1)* | *Q(t)* |
| 3 | *P(t-1) P(t) EVT(t-1) EVT(t)* | *Q(t)* |
| 4 | *P(t-1) P(t) EVT(t-1) EVT(t) Q(t-1)* | *Q(t)* |
| 5 | *P(t-2) P(t-1) P(t) EVT(t-2) EVT(t-1) EVT(t)* | *Q(t)* |
| 6 | *P(t-2) P(t-1) P(t) EVT(t-2) EVT(t-1) EVT(t) Q(t-2) Q(t-1)* | *Q(t)* |

*P*: mean monthly precipitation (mm/month); *EVT*: potential evapotranspiration (mm/month); *Q*: mean monthly discharge ($m^3/s$).

The procedures in the partial report 04 were repeated for all nine sub-basins.

The first step into the monthly rainfall runoff model development was to build a model which determined the best Artificial Neural Network (ANN) to each sub-basin in the Brazilian area of the La Plata Basin. To do so, the model was trained and simulated with historical data. In the table 02 the best ANN to each basin was shown as a result. The ANNs of each sub-basin differs in the type of the input data, number of neurons in the middle layer, number of epochs (iterations), and the size of the input data.

**TABLE 02 - THE BEST MODELS SELECTED BY WATERSHEDS**

| number | basin | model | ARC | EPOCH | INICIAL |
|---|---|---|---|---|---|
| 1 | Alto Paranaiba | 2 | 10 | 60 | E |
| 2 | Baixo Paranaiba | 4 | 8 | 60 | E |
| 3 | Alto Grande | 2 | 10 | 30 | E |
| 4 | Baixo Grande | 4 | 8 | 60 | E |
| 5 | Tietê | 4 | 8 | 30 | B |
| 6 | Parapanema | 4 | 8 | 30 | B |
| 7 | Iguaçu | 4 | 8 | 30 | B |
| 8 | Uruguai | 4 | 8 | 60 | E |
| 9 | Paraná | 4 | 3 | 30 | B |

The second step, developed for this report, was to create a different model to each sub-basin, using the best ANN which was chosen in step one. These models use historical data in the training process and the future data (based on the future scenarios) in the simulation process. The inputs in these models are precipitation, evapotranspiration and previous runoff and the outputs are the runoffs for the future months.

## 2. Computer programs developed – TASK D9.18

### *2.1 Introduction*

Project CLARIS aims at evaluating the impact of climate changes on the Water Resources Systems performance, and this part of the studies concentrates mostly on hydropower generation. This item of the report is on the computational routine development that will be employed at investigating the climate changes influence on the firm energy of the Brazilian South and Southeast/Middle west interconnected hydropower plant systems.

Natural Energy Hydrograph Method: Computational Routine Development
The studies were divided into the following steps:

1. Data collection
2. Raifall-runnof model – see item 1.
3. Multivariate Rain Generation Model
4. Aggregation Routine
5. Statistical Routine (supporting the Multivariate Rain Generation Model)
6. Generation Routine
7. Simulation Routine

### *2.2 Data Collection*

Data were collected from several databases for the catchment areas of interest. Namely, they are the large basins of the Brazilian South, Southeast and Middle West Regions. The large hydropower plants are located in those regions. Setting up a specific database for the project and validation of the developed routines were accomplished with this information.

### *2.3 Multivariate Rain Generation Routine*

A mathematical model was developed to generate synthetic annual rain series that were further disaggregated on a monthly basis (Kelman, 1987). The routines were implemented in Matlab™ language (Hanselman, 2003; R12 v. 6.0.0.88). The figure 1 shows the scheme of this model.

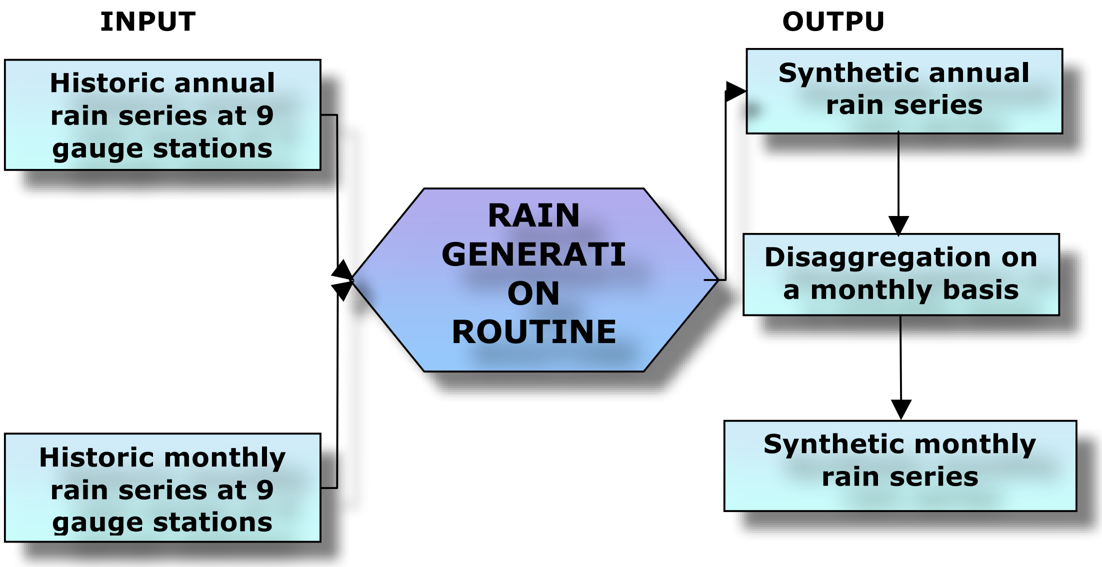


**Figure 1 – Scheme of Multivariate Rain Generation Routine**

### *2.4 Aggregation Routine*

The aggregation model, or aggregation routine, transfers the inflow data from significant places to those where there are hydropower plants. Then, they are transformed into natural energy input by means of appropriate transformations. The sum of all natural energy inputs to a specific system is consolidated into the system natural energy.

The same procedure is applied to the active storage levels, which are aggregated into a single large energy reservoir. This reservoir is then called equivalent reservoir. This aggregation method was firstly employed by the study group named CANAMBRA, 1966 & 1969.

The aggregation routine was implemented in Pascal language following the structure presented in figure 2:

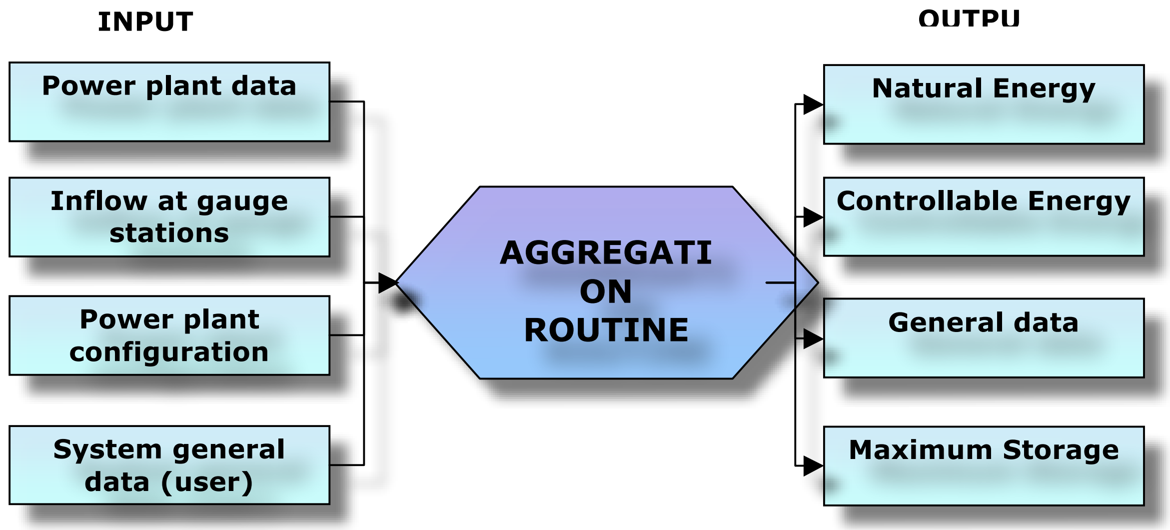


**Figure2 -Aggregation Routine Input & Output**

***2.5 Statistical Routine***

In order to generate synthetic natural and controllable energies one must first transform the energy sequences into normally distributed values. Therefore, one must compute the following parameters: mean, variance, third moment (skewness), fourth moment (kurtosis), and covariance. Also, the parameters autocorrelation lags 1, 2 and 3; median; minimum, maximum and standard error.

One must also adjust the natural and controllable energies in order to obtain stationarity. This can be accomplished in the following manner:

First, two different time periods are chosen, and then one has to perform a linear approximation to the accumulated energy series along those periods employing the least squares method. The correction is done for the annual and monthly series only for the first period of time. That is to say,

$$\mathrm{E}(t) = \frac{mk_2}{mk_1}\mathrm{E}(t)$$

| | | |
|---|---|---|
| $\mathrm{E}(t)$ | - | Energy series |
| $mk_1$ & $mk_2$ | - | Angular coefficients of the linear least square approximation with respect to periods 1 & 2 |

The statistical routine was implemented in Pascal language. The scheme of the program is show by figure 3.

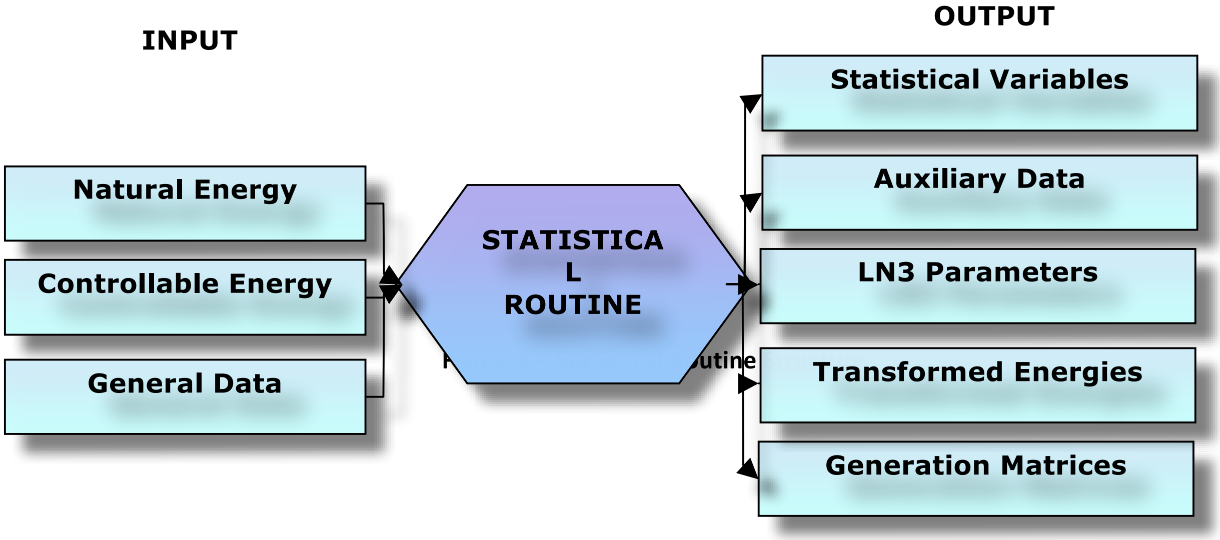


**Figure 3 – Statistical routine structure**

*2.6 Generation Routine*

The routine uses a mathematical model based on the principles of Fill (1980) in order to create synthetic series of annual disaggregation on a monthly basis energy which is natural and controllable.
The generation routine was developed in the Matlab software (Halselman, 2003; R12 v. 6.0.0.88). Figure 4 shows the scheme of the program.

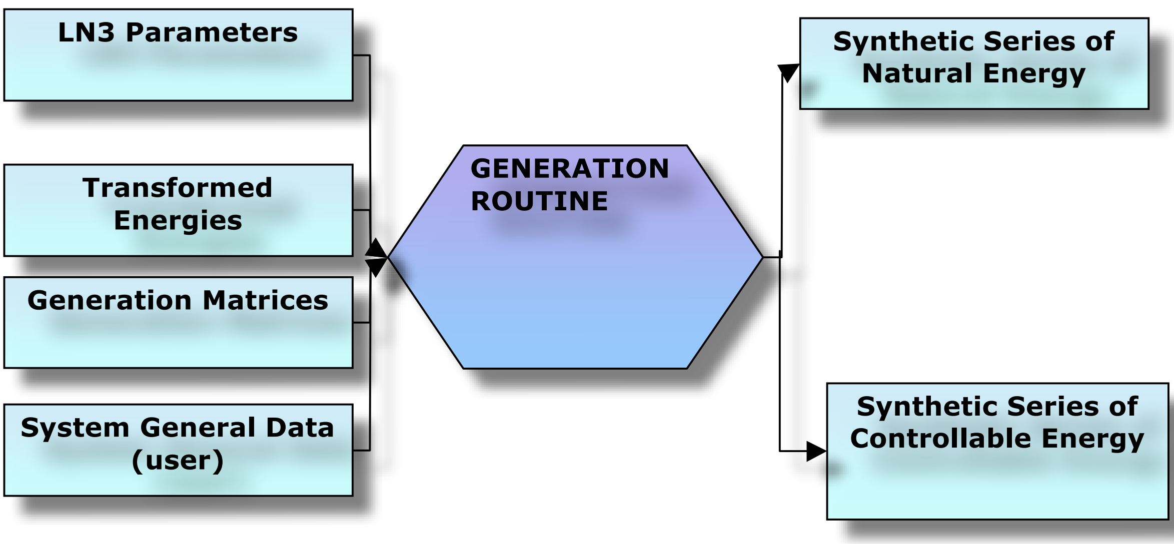


**Figure 4 – Generation Routine Structure**

### *2.7 Simulation Routine*

The Simulation Routine calculates the firm energy for each series. It is also responsible for providing a relation between guaranteed energy and risk. This can only be accomplished using the maximum storage and the synthetic natural and controllable energy series (obtained through the statistical characteristics of the natural energy series by the Generation Routine).
The model´s algorithm can be reduced as follows:

$$D = \left[\sum E(t)\right]/T$$

1) $A(0) = A_{\max}$

$$Para \quad t = 1,2,\ldots,T$$

$$A(t) = \min\begin{cases} A(t-1) - D + E(t) \\ \mathrm{A}(t-1) + \mathrm{E}_c(t) \\ A_{\max} \end{cases}$$

$$se: \quad A(t) = A_{\max}: \quad n = 0$$

$$senão \quad n = n + 1$$

$$\begin{cases} se \quad A(t) < erro \\ D = D + A(t)/n \\ Volta \quad para \quad 1) \end{cases}$$

$$E_{f\,irme} = D$$

The routine is also represented on Figure 5.

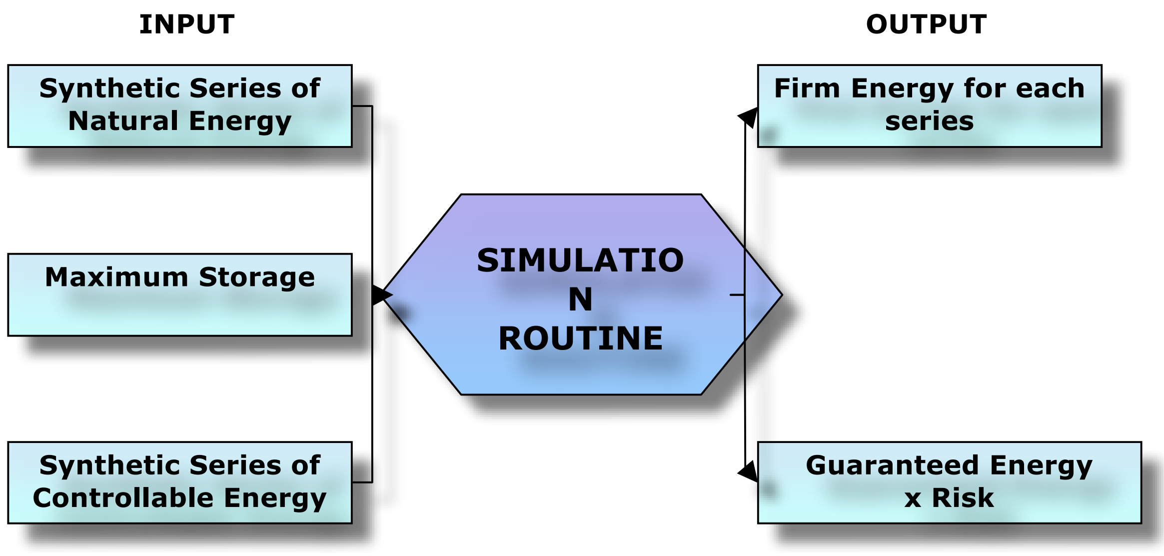


**Figure 5 – Simulation Routine Structure**

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