A Neural Network Approach for Generating Solar Irradiation Artificial Series

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ABSTRACT

In this paper a relevant problem in the photovoltaic solar energy field is considered: the generation of artificial series of hourly solar irradiation. The proposed methodology artificially generates series following the average tendency of the hourly radiation series k_t in a given place. This is obtained by making use of a set of historical values of this series in such place (for training purposes) as well as the *daily* clarity index K_T of the year to be generated. This information is employed for the supervised training of a proposed neural network model. The neural model employs a well known paradigm, called Multilayer Perceptron (MLP), in a feedback architecture. The generation method is based on the MLP ability to extract, from a sufficiently general training set, the existing relationships between variables whose interdependence is unknown a priori. This way, the presented design methodology can implicitly include all the available information. Simulation results show the good performance of the irradiation series generator, and the general applicability of this methodology in the estimation of highly complex temporal series.

1 Introduction

The design and analysis of *photovoltaic converters* is usually performed via numerical simulations which require as input data large time sequences of *hourly or daily irradiation** values [Grah 90, Lore 91]. Nevertheless, these historic radiation measurements do not exist in most of the world countries, and, if any, their quality is questionable or they have plenty of missing values.

In 1988 Graham proposed the substitution of this historical measurements by *synthetic sequences* of irradiation values generated using mathematical models of the irradiation process. These generated sequences should preserve the statistical properties of the historical measurements. The proposed methodology was based on autoregressive time series theory for generating sets of *daily* values of solar irradiation.

The work described in [Grah 90] extends such methodology to the generation of *hourly* solar irradiation series making use of daily values. These daily values can be obtained from historical measurements (which are more common than hourly measurements) or via some daily values generation methods (which are more validated than hourly methods). This is an *stochastic disgregation* method (very typical in *Hydrology*: to separate the annual flow estimation into monthly estimations). The hourly radiation series are very useful when studying photovoltaic systems with one or two-hour response time such as *peak plants* or photovoltaic plants which return energy to the network at maximum charge instants.

The main criticisms to Graham's method are the *high computing requirements* for obtaining each series value, and the *geographical location dependency of the method* with the place where data has been retrieved for constructing the model.

In this work, we propose a neural network approach, making use of the Multilayer Perceptron (MLP) [Lipp 87, Rume 86, Werb 74] in a feedforward-feedback architecture [Nare 90] for generating hourly solar radiation series. The main attractive property of our method is the MLP capability for approximating any continuous function defined on a compact set within a prescribed error margin. Existence results prove that it suffices to employ a MLP with a hidden layer, a required number of neurons and an appropriate training procedure [Horn 89]. In practice, selection of appropriate topology as well as training algorithms may become a big challenge.

One important aspect addressed in this paper is the possibility of employing the presented architecture with a reduced knowledge of the problem to be considered . In that sense the paper defines a simple design methodology with quite general applicability.

The paper is organized as follows. Section 2 presents some basic aspects concerning the use of MLP based architecture for time series processing; in addition, specific aspects related with the generation of irradiation series are also considered. The specific proposed model for the generation of time series is presented in section 3. Concluding remarks are outlined in section 4.

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*The term solar *radiation* refers to the physical phenomenon in a generic sense, whereas the term *irradiation* refers to the incident energy on a horizontal surface over a given period of time (hourly, daily irradiation, etc). Therefore, the irradiation units are $\frac{kw \cdot h}{m^2}$.

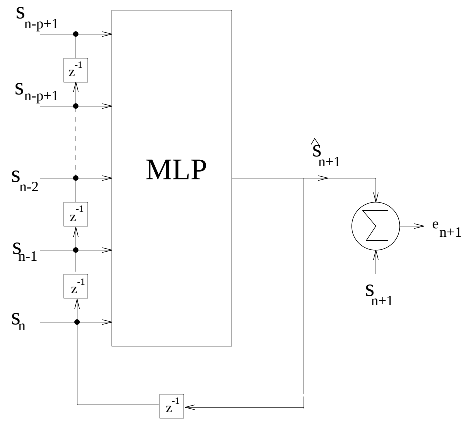

Figure 1: Prediction *via network evolution.*

2 Methodology for design of MLP based architecture

2.1 The Multilayer Perceptron

Since several years ago, neural networks are increasingly used in different scientific and technical fields [Agar 97, Hayk 94, Hush 93, Koho 95, Lipp 87]. For instance, as a computation and learning paradigm, they can be used for many types of applications. One of the most appealing properties of some neural network paradigms is their potential use for functional approximation purposes [Horn 89]. The Multilayer Perceptron (MLP) is the most widely used type of neural network for approximation tasks; it is classified as a feedforward type neural network, whose topology defines several layers of neurons. The MLP, in static contexts, is usually trained via a supervised procedure, one of the great advantages of the MLP being the existence of a very efficient training method for it: the backpropagation algorithm [Rume 86, Werb 74].

Also, in dynamic contexts, the identification and control of nonlinear plants, as well as the time series prediction have been successfully addressed via feedback architectures of supervised neural models [Nare 90, Nare 91, Weig 90]. This work can be framed in such context, as shown below.

2.2 MLP for time series prediction

The methodology employed for Times Series Prediction (TSP) and system identification via MLP [Lape 87, Nare 90, Nare 91, Weig 90, Vazq 92] is the framework of the method developed for generating hourly solar radiation series.

The problem of TSP via MLP makes use of the time series $\{s_n\}$, for obtaining the function $\mathcal{G}$ (in case that such function exists) which relates each series value with the previous p values:

$$\hat{s}_{n+1} = \mathcal{G}[s_{n-p+1}, ..., s_n] \simeq MLP[s_{n-p+1}, ..., s_n.] \qquad (1)$$

By training a MLP with p inputs and 1 output, with a training set representative enough, the MLP will be able to find the desired relationship (in case that it exists) just approximating the function $\mathcal{G}$. Once the approximation is performed, *future* values can be computed via feedback of the predictions whenever they are available. Such method is called *prediction by network evolution* (see Figure 1).

One of the great advantages of employing a MLP based methodology for generating radiation series is that most of the computational resources are required during the training procedure, as opposed to the generation procedure. In addition, once the method is developed from historical data of a prescribed place, it can be applied to new places just by repeating the training procedure with new data corresponding to such new places.

2.3 The nature of the information

The procedure shown in this paper makes use of *atmospheric transmittance or transparence* values (as in Graham's work) instead of a direct use of solar irradiation values. This transmitance (also called *clarity index*) is represented as k_t for hourly values and K_T for daily values. The extraatmospheric solar irradiation behaves in a deterministic way and it is the clarity index which induces randomness to the solar irradiation measured on earth. More precisely:

$$k_{t_h} = \frac{G_h}{Bo_h} \in [0, 1] \tag{2}$$

where Bo_h is the extraatmospheric irradiation on a horizontal surface during hour h, and G_h is the irradiation during hour h on the earth surface. Also, the solar irradiation variable is specific for a given place whereas the random properties of the clarity index behave in a quasi-universal manner.

The progression of k_t values could be described from a distribution probability function if such hourly events were to be independent. Since this is not the case, additional information is required of the *correlation* between different hourly values. Nevertheless, the progression of k_t cannot be described via an *stochastic process* (which is a necessary condition for applying ARMA models [Prie 88]), because the probability associated with daily events changes in a monthly manner (i.e., there exists some *monthly stationality*) and the probability associated with hourly events changes every hour (there exists *hourly stationality*). In addition, the probability of a given k_t to happen depends on the clarity index K_T of the referred day.

In our computational experiments we made use of a set of hourly irradiation values k_t measured in Madrid between 1978 and 1986. Such set of data corresponds with 9 (years)$\times$365 (days per year) $\times$16 (measured hours per day) values of k_t and its corresponding 9×365 daily values K_T.

As a first approach to the problem, due to the limitations for evaluating the quality of a generated series, we considered the first 8 years as a *training set*, and employed the 9th year for testing the validity of the generated series. We measured such validity with the parameter *Mean Relative Variance* (MRV), which quantifies the relative error and is frequently employed in the Digital Signal Processing community. The MRV defines an estimation of the quotient between the *prediction error signal power* and the *AC power of the signal to be predicted*:

$$MRV = \frac{\frac{1}{l}\sum_{i=1}^{l}(s_i - \hat{s}_i)^2}{\frac{1}{l}\sum_{i=1}^{l}(s_i - \bar{s})^2} \tag{3}$$

2.3.1 Information inclusion

The proposed method for generating hourly radiation series has been developed via an step-by-step inclusion of the available associated information. The great advantage of this MLP based methodology is that explicit knowledge of the relationship among all the information sources is not needed. Such information sources can be progressively incorporated in different steps upon the proposed method. The details of this step-by-step procedure can be found in [Vazq 93].

3 Proposed generation method

The generation procedure proposed in this paper can be seen in Figure 2. A MLP is employed in a mixed feedback-feedforward configuration.

As a first step, the series of $9 \times 365 \times 16$ values was considered as a numeric sequence, without making use of the meaning of its indexes (which hour of day or which day of the year they refer to). A MLP was trained with the series corresponding to the 8 first years and the 5840 values corresponding to the 9th year were generated in an iterative manner by application of *prediction by network evolution* (see Figure 1). As expected, the results were not satisfactory; this first approach does not provide good results, showing the need of employing additional information.

Consequently, daily information was considered. A *day by day* prediction method was employed as well as a dependency of any hourly value with the three previous hours of the same day Therefore, in order to generate the 16 hourly values $\{k_t\}$ of a given day, we started a method of prediction by network evolution with window $p = 3$. This implies the need of using the k_t values of the 3 first hours of such day. Since these three initial values are 0 (or close to 0) for most of the days of a year, it is reasonable to assume that they do not provide meaningful information. In addition, these values can be modeled in a probabilistic framework.

In order to keep the *monthly stationality*, a new input was added to the MLP containing the distance (days) between the value to be generated and the day with maximum value in the $\{k_t\}$ annual distribution. The *normalized day* input was defined as $d_n = 1 - \frac{|N_d - 163|}{163}$, where N_d is the day number within the year.

In a following step a new MLP input was created indicating the value of the daily clarity index K_T corresponding to the day to which the hourly to-be-generated value belongs. These 365 K_T values were taken from the year to be generated (9th year of our data). In a real application of the method, a method for generating those 365 K_T values would be first employed, generating the 5840 hourly values afterwards.

The final step of our method added a new input to the MLP indicating the *hour order number* of the k_t value to be generated. This value, ranging from 4 to 16, in size 3 window, is normalized upon $hour_{norm} = \frac{hour - p}{16 - p}$, where p is the prediction window size.

It is important to note that different optimization schemes were employed for the supervised training of the networks studied. Although some schemes did improve the performance, the proper selection of the neural model inputs showed to be the most relevant design issue.

In order to test the quality of the method, hourly values series were generated for each the 9th year having employed the previous 8 years in the training procedure. In

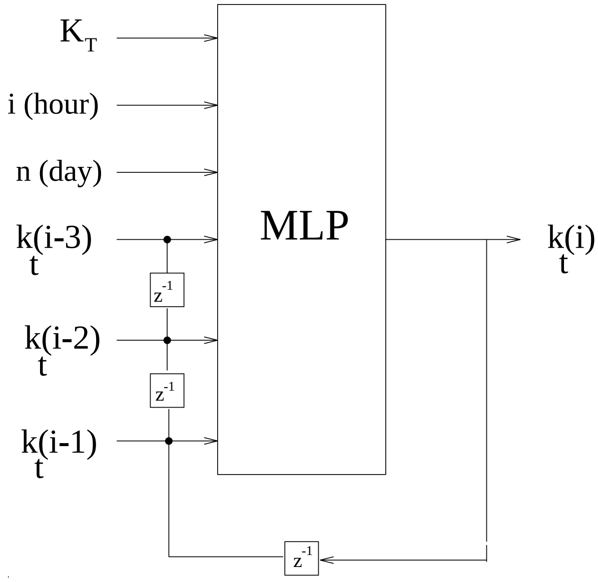

Figure 2: Proposed generation method.

order to generate it, 365 K_T (daily clarity index) of such year were needed as inputs, as well as the 3 initial values of the hourly clarity index k_t of each day. The MRV obtained was 0.0943, proving that the method emulates quite well the deterministic component of the series.

The obtained series generator can be successfully compared is some aspects with the computation of the *average tendency* k_{tm} performed by Graham's method. Our proposed method can be employed for generating series corresponding to any locality, if the corresponding training data set is available, i.e. a set of *hourly* and *daily* clarity indexes measured over several years. Also, Graham's method requires the same training set for computing the *nonlinear regressions* corresponding to each locality which link each hour k_{tm} value and the K_T value of the corresponding day. On the other hand, the use of a MLP does not assume any a priori model, being advantageous versus a nonlinear regression approach.

From an academic point of view it is very interesting to note tha MLP capability for finding relationships among variables of different nature. In our example, making use of an appropriate training set, the MLP was able to relate information from *hour of the day*, *daily clarity index* value, and 3 previous values of the *hourly clarity index* in order to generate a new k_t index value.

Nevertheless, the shape of the resulting series does not have the characteristic rippling of the real series. This is due to the fact that the employed training set (8 years of k_t and K_T values) was large in relation to the MLP 5-x-1 topology. It is possible that such training set may have input/output pairs such that different *desired output values* may be linked with the same input value. Therefore, after training the MLP, an averaging effect might have occurred among such different output values. Hence, this could justify that our proposed method does not generate radiation hourly series with the characteristic stochastic rippling of the real series (the generated series are smooth as can be seen in Figure 3).

For the sake of emulation completeness, the stochastic rippling was emulated, as a first approach, via a generated set of random gaussian variables corresponding to the 16 hours of the day excluding the initial p and last 2 (that is $16 - p - 2$ random

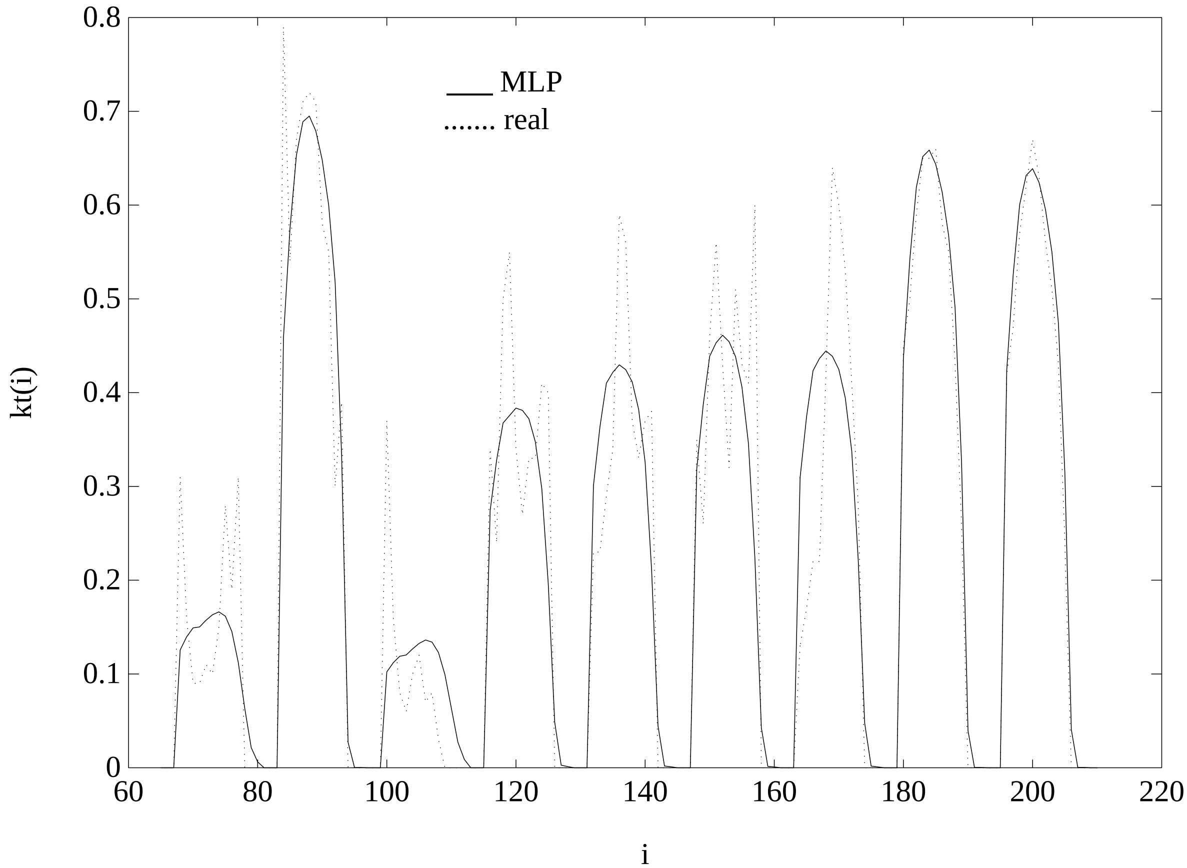

Figure 3: Real series versus generated one without noise. Days 5-13.

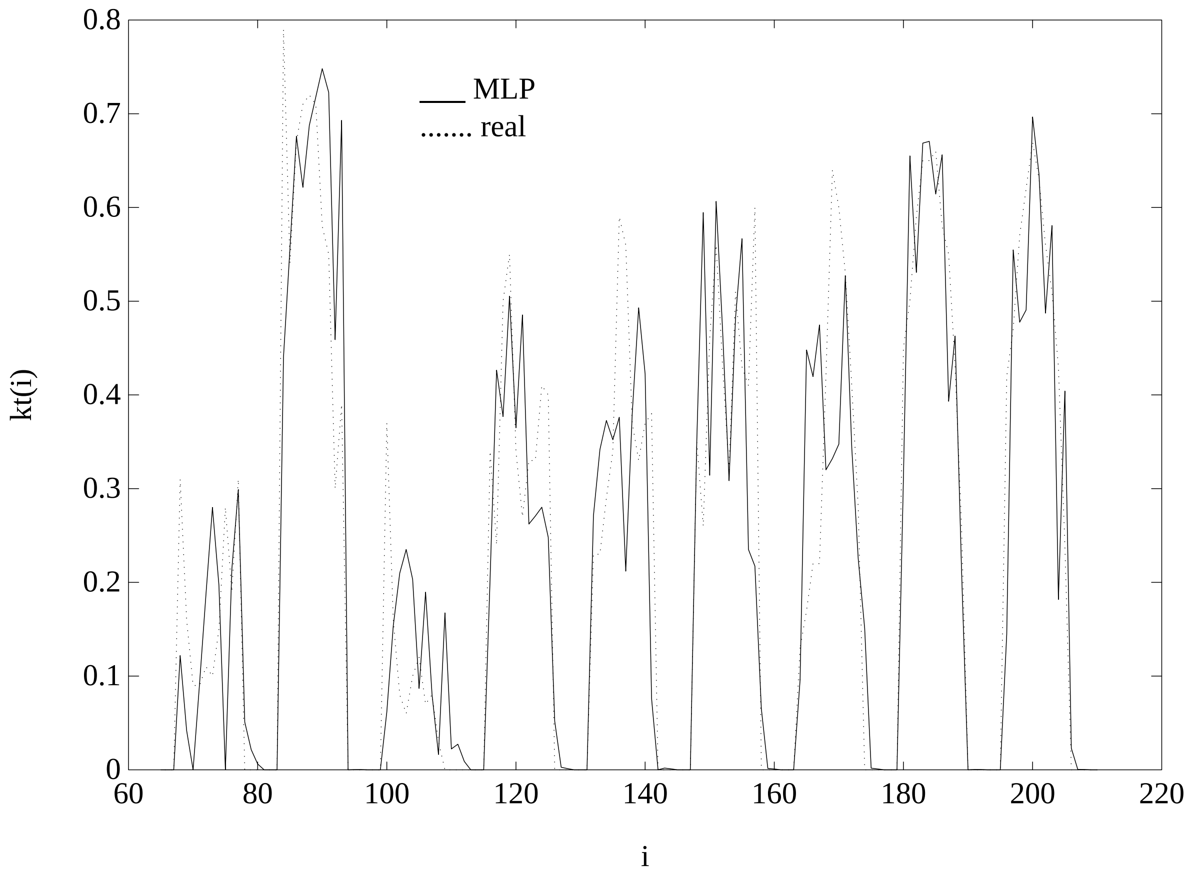

Figure 4: Real series versus generated one with additive noise. Days 5-13.

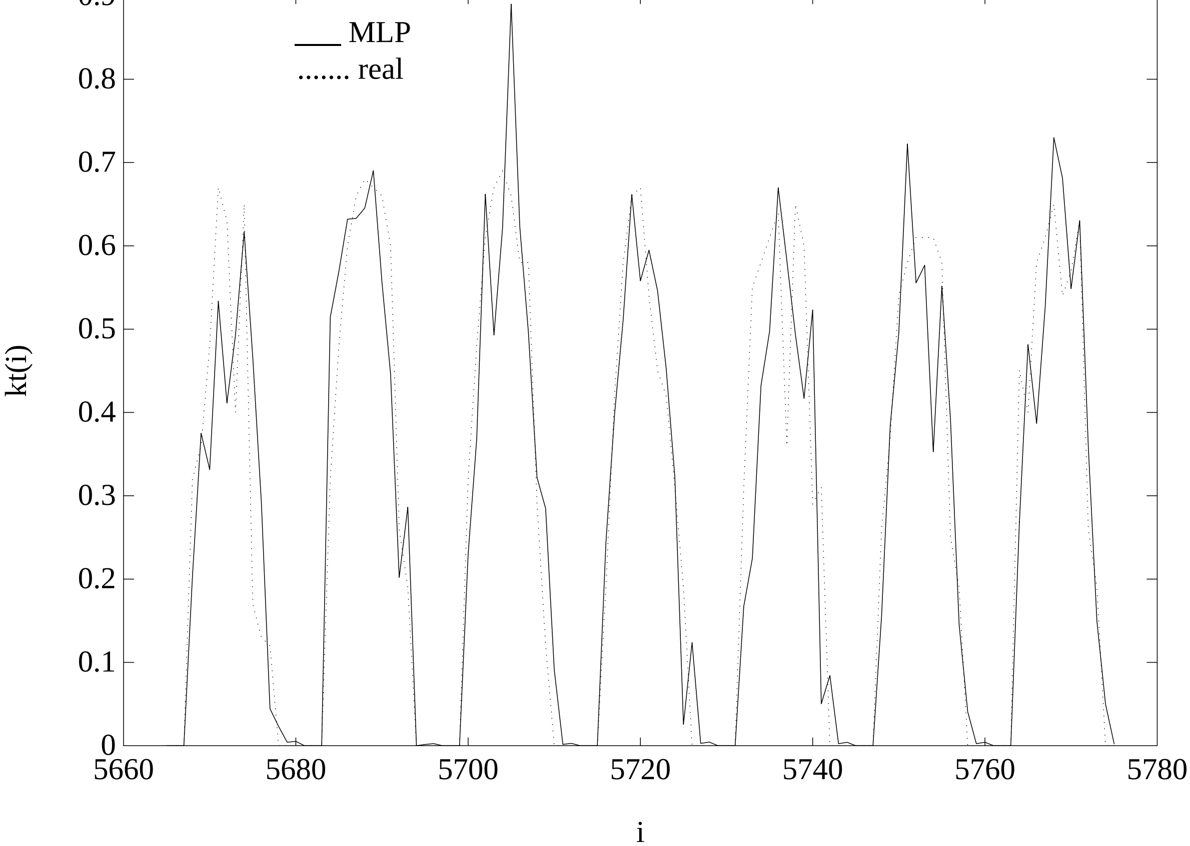

Figure 5: Real series versus generated one with additive noise. Days 355-361.

variables). The means and variances of these random variables were estimated from an error signal between the 9th year real series and the series generated by our proposed method. Hence, we added to each of the generated hourly series values $\{k_t\}$ one realization value of the random variable corresponding to such hour. The initial 3 hours of each day and the last 2 did not suffer such perturbation. In Figures 4 and 5 we show the series corresponding to the 9th year, generated by the described method after adding the noise, corresponding to the hourly values from day 5 to 13, and from 355 to 361 respectively.

4 Concluding Remarks

A methodology based on neural networks has been presented for generating time series following the average tendency of the hourly radiation series k_t in a given place. Such methodology is based on the possibility of implicitly employing information associated with the problem, without knowing the existing relationships between different variables and sources of information.

The proposed methodology makes use of both a set of historical values of the series (for training purposes) as well as the *daily* clarity index K_T of the year to be generated in a straightforward manner: the whole information has been employed for the supervised training of a MLP based feedforward-feedback architecture. A proper selection of the model has proved to be more critical than the training method selected.

Although the quality of the developed method needs further testing, one can conclude that the generation can be performed with *little knowledge of the problem*. This is due to the MLP capability for *finding relationships* among variables with unknown a priori relationship. Nevertheless, a proper MLP topology and training set must be selected for such purpose.

The proposed method does not assume any a priori model as opposed to the standard approximation techniques where polynomial regression techniques are employed.

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