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Local Meteorological Forecasting by Type-2 Fuzzy Systems Time Series Prediction

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Abstract – *Meteorological forecasting is an important issue in research. Typically, the forecasting is performed at "global level", by gathering data in a large geographical region and by studying their evolution, thus foreseeing the meteorological situation in a certain place. In this paper a "local level" approach, based on time series forecasting using Type-2 Fuzzy Systems, is proposed. In particular temperature and humidity forecasting is inspected. The Fuzzy System is trained by means of historical local time series. The procedure uses a frequency signal decomposition in order to extract chaotic and deterministic components, so as they be independently predicted. This technique allows us to achieve more accurate forecasting results even many hours in advance.*

Keywords – *Forecasting, time series prediction, signal decomposition, Type-2 fuzzy systems.*

I. INTRODUCTION

The recent evolution of the power computation of the modern computers has allowed a great improvement in the field of meteorological forecasting. Typically, it is performed at "global level", gathering a huge amount of data over a large geographical region. The study of the evolution of this data permits to foresee the meteorological situation in a certain place. Because of the large amount of data to be processed, this procedure is time consuming and needs very powerful computers. On the contrary, a complementary approach permits to operate at "local level", processing only the historical data related to that place in order to predict its future evolution. Many meteorological variables, such as the temperature, the humidity, the pressure, the wind speed can be taken into account and analyzed. The sampled values of the interesting variables are acquired in uniformly spaced intervals and used to predict one or more samples in the following intervals. This procedure is known as "Time Series Prediction". It is composed of two phases. In the first one the prediction system is trained using known time series. In the second one the following value is predicted starting from a certain number of previously acquired samples. Many approaches for the prediction systems design have been proposed in literature. Some of them exploit analytical properties of the series and compute the following values starting from a proper expansion of the signal. Others consist of a neural network trained on previous historical values [9].

Our approach uses a particular Fuzzy Logic System (FLS), known as Type-2 FLS, suitable to take into account non-stationary noise both in the training and operating phases. Moreover, a deep analysis of the signals has allowed an accurate prediction in coming time intervals.

The paper is organized as follows. In Section II Type-2 FLS are pointed out in order to show how they can be used in forecasting. In Section III the time series prediction issue is explored and in Section IV a particular set of meteorological data, acquired during a year, are analyzed in order to identify its components in time and frequency domains. In Section V the architecture of the whole system is described and Section VI shows preliminary simulation results. Finally, in Section VII some aspects of the proposed approach will be highlighted.

II. TYPE-2 FUZZY LOGIC SYSTEMS

A classical FLS, also denoted as Type-1 FLS, can be represented as in Fig. 1. As shown, rules play a central role in the FLS framework. Rules can be provided by experts or can be extracted from numerical data. The IF-part of a rule is an antecedent while the THEN-part of a rule is its consequent. Fuzzy sets are associated with terms that appear both in the antecedent and in the consequent, while Membership Functions (MFs) are used to describe these fuzzy sets. Recall that a Type-1 fuzzy set A, can be represented, in terms of a single variable $x \in X$, as

$$A = \{(x, \mu_A(x)) | \forall x \in X\}$$

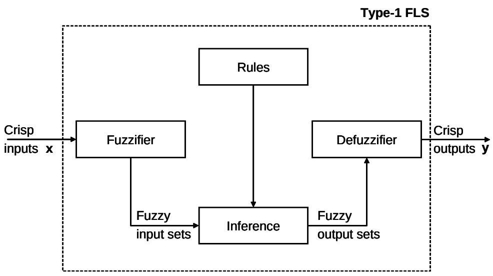

Fig. 1. Type-1 FLS scheme

where Type-1 MF, $\mu_A(x)$, belongs to the range $[0,1]$, for all $x \in X$ and it is a 2D function, that depends on both x and A.

In order to introduce the reader to the concept of Type-2 fuzzy sets, let us consider firstly the transition from ordinary sets to fuzzy sets. When we cannot determine the membership of an element in a set as 0 or 1, we use fuzzy sets of Type-1. Similarly, when circumstances are so fuzzy that determining the membership degree even as a crisp number in $[0,1]$ is a difficult task, we use fuzzy sets of Type-2, a concept that was first introduced by Zadeh in 1975 [1]. Thus, when something is uncertain (e.g. a measurement), we have trouble determining its exact value, and in this case we need Type-1 fuzzy sets, instead of crisp sets. But, if we cannot determine its exact value, how can we determine its exact membership in a fuzzy set? So, ideally we need to use Type-∞ fuzzy sets to completely represent uncertainty, but in practice we have to use some finite-type sets, just like Type-2 fuzzy sets.

Imagine blurring the Type-1 membership function depicted in Fig. 2 (a) by shifting the points on the triangle either to the left or to the right and not necessarily by the same amounts, as in Fig. 2 (b). Then at a specific value of x, x', there no longer is a single value for the membership function, whereas the membership function takes on values wherever the vertical line intersects the blur. Those values need not all be weighted the same, and we can assign an amplitude distribution to all of those points. So we can create a three dimensional membership function, a Type-2 MF, that characterizes a Type-2 fuzzy set. Thus we can define a Type-2 fuzzy set $\tilde{A}$ as follows

$$\tilde{A} = \{(x,u), \mu_{\tilde{A}}(x,u) | \forall x \in X, \forall u \in J_x \subseteq [0,1]\}$$

where $\mu_{\tilde{A}}(x,u) \in [0,1]$. From this definition it follows that fixed $x = x'$ we have a set of possible values, even with different weights, that we call *secondary MF*, $\mu_{\tilde{A}}(x',u)$, while the domain of this secondary membership function is called *primary membership* of x, J_x in the expression above. Consequently we have primary and secondary degree of membership to a fuzzy set. Fig. 2 (c) represent the set of all possible primary MFs embedded in a Type-2 fuzzy set, also denoted as *Footprint of Uncertainty (FOU)*. This term seems very useful because it provides a convenient way to describe the entire support of the secondary grades and in many applications allows to correctly choose appropriate MFs by first thinking about their appropriate FOUs. The FOU can be also described through the concepts of *lower* and *upper* MFs [2] that represent respectively two Type-1 MFs that are bounds for the FOU of a Type-2 fuzzy set $\tilde{A}$. An example is provided in Fig. 3.

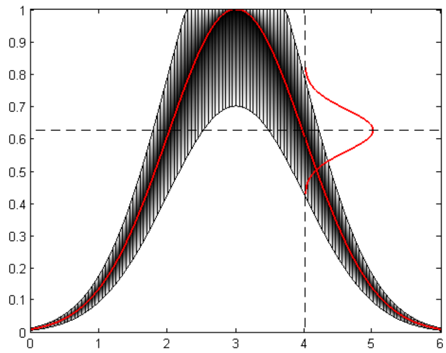

Fig. 3. Footprint of Uncertainty

Many choices are possibile for the secondary MFs, Gaussian, triangular, trapezoidal, etc. In particular when the secondary membership degree of x is rectangularly shaped, we say that the secondary MFs are *interval sets*, so that Type-2 FLS is also denoted as *Interval Type-2 FLS* [3]. This subclass of Type-2 fuzzy sets makes this new set of systems more attractive owing to a substantial simplification in the characterization and in the tuning of its parameters. In fact, despite of the growing importance of this class of FLS [4], characterizing a Type-2 FLS is not as easy as characterizing a Type-1 FLS. In fact, by computational aspects, the main difference between Type-2 FLS and Type-1 FLS is in the output processor, as shown in Fig. 4. While the output stage in Type-1 FLS is just a defuzzifier and produces a single value as output, the output stage of a Type-2 FLS can be further subdivided in the cascade of two blocks: the first one maps a Type-2 set into a Type-1 set (type reduction [5, 6]) and the second one is a classical defuzzifier. In order to emphasize the difference between classical Type-1 FLS and Type-2 FLS note that the output of a Type-1 FLS is just like the mean of a unknown probability density function (pdf), while a Type-2 FLS can provide information about the dispersion around this mean, just like a variance of that pdf. Despite apparent simplicity, also common operations of union,

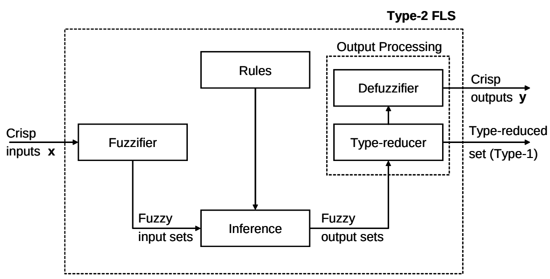

Fig. 4. Type-2 FLS scheme

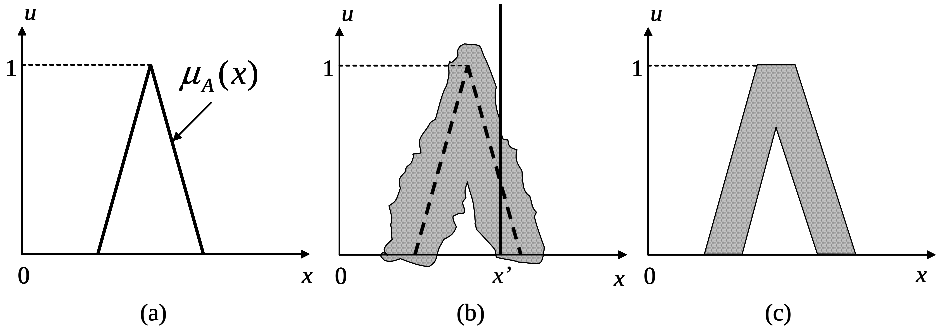

Fig. 2. (a) Type-1 MF, (b) Blurred Type-1 MF, (c) FOU

intersection and complement, needed to implement a classical Type-1 FLS, must be readapted.

During recent years, many works have examined and proved interesting properties of Type-2 FLS making them an effective tool in many classical fields, such as control of mobile robots, decision making, forecasting of time series, function approximation, preprocessing of radiographic images, transport scheduling, co-channel interference elimination from nonlinear time-varying communication channels [5, 7]. In particular, forecasting is a very important issue that appears in many disciplines. For example weather forecast can save lives in the event of a catastrophic hurricane, or financial forecasts can improve the return of an investment. The problem of forecasting a time series can be formalized as follows:

Given a set of p past measurements of a process $s(k)$, namely $x(k-p+1)$, $x(k-p+2), \dots, x(k)$ determine the estimate of a future value of s, $\hat{s}(k+l)$, where p and l are fixed positive integers.

If the measurements are noise free, then the set of past values are replaced by $s(k-p+1)$, $s(k-p+2), \dots, s(k)$. When $l = 1$ we obtain the single stage forecaster of s, while in general we obtain the l-stage forecaster of s. Suppose now we collected N data points, $x(1)$, $x(2), \dots, x(N)$, then we must divide them in two set: the *training* data subset $x(1)$, $x(2), \dots, x(D)$ and the *testing* data subset $x(D+1)$, $x(D+2), \dots, x(N)$. Because we use p data points in order to estimate the next data point, we will have $D-p$ training pairs. The training data can be used in order to establish the rules of the FLS in at least two ways.

- The data are used to initialize the center of the fuzzy sets both in the antecedents and in the consequents of the rules.
- A possibile architecture of the FLS is chosen and the training data are used to optimize its parameters.

What makes a Type-2 FLS more suitable to deal with this kind of applications is the fact that commonly the collected data, used both as training and testing data, are affected by (even non-stationary) noise and above all contain at least one intrinsic chaotic trend, spreading in different ample regions of the spectrum of the signal. This fact arises from the intrinsic chaotic nature of meteorological times series. Both these reasons justify the fact that a classical Type-1 FLS does not succeed in handling the intrinsic uncertainty that the data hold, thus provoking a local drift of the short-term predicted values whereas a notable error in long-term prediction. The concept of *embedded* Type-1 FLS in Type-2 FLS [4] deals with the capability of Type-2 FLS of considering and handling the dispersion of the values of the measurements around a mean, easily predictable, data.

III. TIME SERIES PREDICTION

Time series represent a certain phenomenon time evolution, usually by uniformly spaced time intervals. Many physical, economic, and biological phenomena can be represented by time series. They can be classified basing on the relation between the time dependent variable and the time itself. Often, in real cases, a certain phenomenon is described by a discrete time series rather than a continuous time series because the measurements acquired to characterize it are obtained as regularly separated samples during the time.

Time series can be usually modeled as the sum of a deterministic and chaotic component. The first one deals with those characteristics of the observed phenomenon that can be computed analytically, while the second one concerns those parts of the phenomenon that appear as "casual" events. So, such series can be described by a model as

$$z(t) = f(t) + a(t), \tag{1}$$

where:
$z(t)$ is the value of the time series,
$f(t)$ is the value of the deterministic component,
$a(t)$ is the value of the chaotic component.
The deterministic component can be often divided in more fundamental components, namely the *trend* that represents the very long-term series behavior (often it is the mean value of the series), and long- and short-term components that represent the deterministic evolution of the time series along long-time and short-time period, respectively.

All these components are reasonably affected by (even non-stationary) noise resulting from measurements, extraction and data processing. The statistics concerning the analysis and the prediction of such series can use different standard methodologies, such as regressive or Box-Jenkins models [8].

IV. HISTORICAL DATA ANALYSIS

The aim of this paper is to describe a method to predict meteorological phenomena, such as temperature and humidity.

The first phase of the research has been the study of historical time series of meteorological measurements acquired in a certain place during about one year by the Neuronica Lab at the Politecnico of Torino (Italy) and their values are depicted in Fig. 5 and 6. The measurements have been performed every

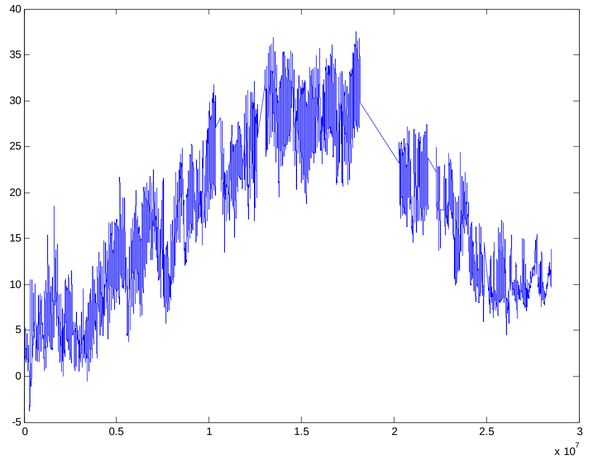

Fig. 5. Temperature trend during one year

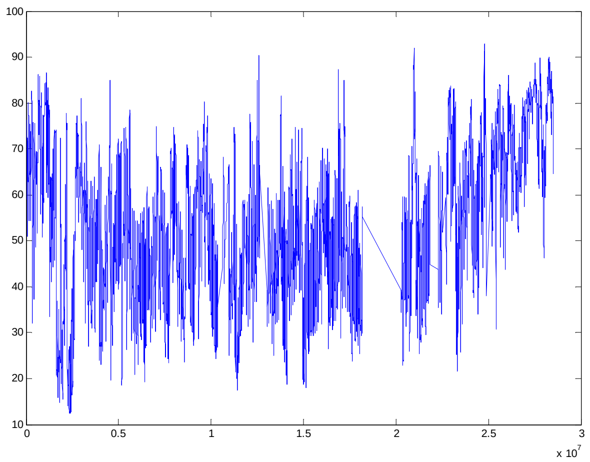

Fig. 6. Umidity trend during one year

900 s, that is a quarter of an hour. This sampling rate is justified by the slow rate of the considered phenomena. Some intervals in which the data are missing, owing to loss of measurements, can be located in graphs.

The first remark we can highlight is the presence of an annual component (more relevant in the temperature time series). The period of this component is obviously exactly equal to one year and corresponds to the trend component of the global signal. So, this is a deterministic component and it can be deleted in order to isolate the others components of the time series. This procedure allows us to avoid biasing in the following steps. Because the very low frequency of this component, that one can suppose sinusoidal (this approximation does not affect the performance of the prediction system), it cannot be deleted through a classical digital filtering procedure. In fact, in this case the filter needs the samples of some periods. That corresponds to acquire samples for some years. The used approach was a sinusoidal regression analysis of the signal in order to detect both the amplitude and the phase of the annual component. Its frequency is in fact obviously known. Once the characteristic of the annual component has been detected, it can be extracted from the global signal.

If we focus our attention on a portion of the time series without the annual component, as in Fig. 7, we can notice the daily component whose mean value waves. This mean value represents the first chaotic component of the time series.

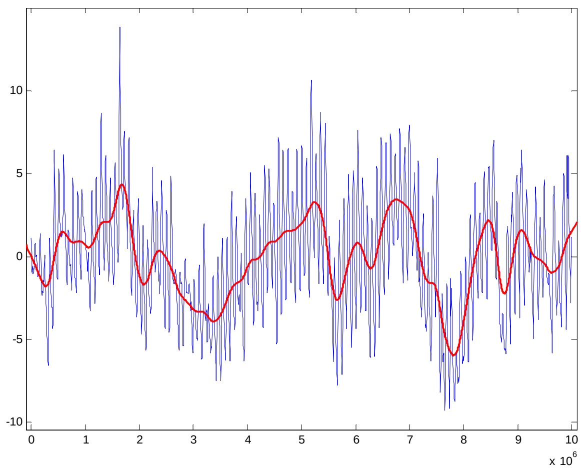

Fig. 7. Chaotic component of the temperature mean value

At this point, it can be particularly useful to inspect the original global signal also in the frequency domain. In Fig. 8 is shown the temperature signal spectrum. One can discriminate the annual component, the daily component (and its harmonics) and other components representing both the chaotic and the noise components of the signal. The frequencies between the annual and the daily components constitute the chaotic signal highlighted in Fig. 7. It can be extracted from the whole signal by a proper filtering procedure.

Once the signal is filtered, only the daily component remains. A portion of it is shown in Fig. 9. As one can note, it appears as an amplitude modulated quasi-sinusoidal signal. The envelop of this signal is a new chaotic signal.

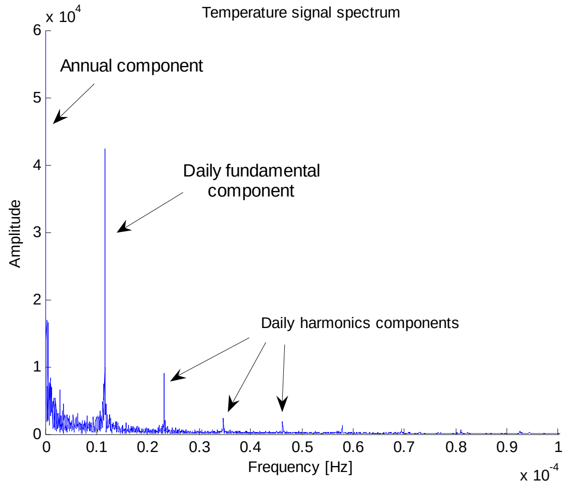

Fig. 8. Temperature signal spectrum

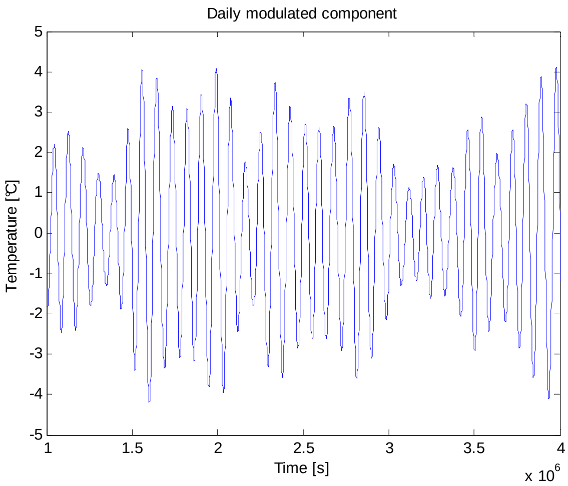

Fig. 9. Daily component of the temperature

Thus, we can summarize that both temperature and humidity time series can be seen as sampled signal having:

1. a quasi-sinusoidal trend component whose period is equal to exactly one year;
2. a chaotic component representing the fluctuations of the mean value of that signal around the trend annual component: it depends on the meteorological events;
3. a daily quasi-sinusoidal component amplitude modulated, whose period is equal to exactly one day;
4. a chaotic component that modulates the daily component.

Components 1 and 3 can be considered as deterministic components, whereas, components 2 and 4 are chaotic components that have to be predicted through a proper forecasting system. So, we have to design two prediction systems in order to estimate the following values of each signal.

V. SYSTEM DESIGN

Starting from the consideration highlighted in Section IV, the whole system depicted in Fig. 10 has been designed. We can identify two Type-2 FLS tuned to predict the chaotic components of the corresponding signal. Two blocks denoted as "Phase and amplitude detection" are used to compute, through a RMS minimization, the parameters of the deterministic components, namely the annual and daily components. This architecture is used for both the training and the working phase. Obviously, each block works in a different way in each phase.

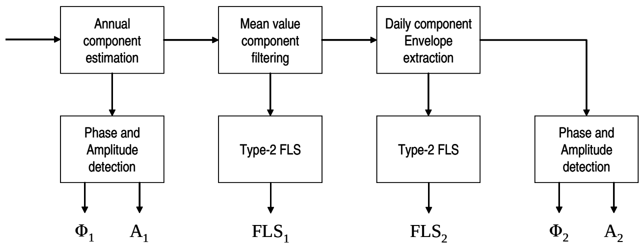

Fig. 10. System architecture

Once the output parameters, shown in the previous block diagram, has been computed, the corresponding variable (e.g. temperature) can be computed as

$$\begin{aligned}\tilde{T}(t) = A_1 \sin(\omega_1 t + \Phi_1) + FLS_1(t) + \\ + (A_2 + FLS_2(t)) \sin(\omega_2 t + \Phi_2),\end{aligned} \quad (2)$$

where $\omega_1 = \frac{2\pi}{P_{year}}$, being P_{year} the number of seconds per year, and $\omega_2 = \frac{2\pi}{P_{day}}$, being P_{day} the number of seconds per day.

$\tilde{T}(k)$ is computed starting from $T(k-p)$ for $p \in [1, 4]$. In the prediction of $\tilde{T}(k+1)$ two ways can be followed. The first one computes $\tilde{T}(k+1)$ from $T(k-1)$, $T(k-3)$, $T(k-5)$, and $T(k-7)$. The second one uses the estimated value $\tilde{T}(k)$ and the previous $T(k-p)$ for $p \in [1, 3]$. The same procedure can be used for the prediction of following values. Each method has different advantages, however the second one has been implemented. It has weakly higher estimation error, but the FLS maintains the same configuration for every following prediction, thus needing only one training procedure. On the contrary, the first approach needs as many training procedures as the number of predictions.

VI. SIMULATION RESULTS

In this section we show some preliminary results of the proposed forecasting approach in the case of temperature prediction, but analogous results have been obtained also in the case of relative humidity prediction.

Figure 11 shows an example of the prediction, performed through a suitably tuned Type-2 FLS, of a portion of the first-type chaotic temperature component vs. the expected behavior. As mentioned above, this component is responsible for a chaotic fluctuation of the mean value of the daily temperature. In the same way, the envelop of the daily temperature has been

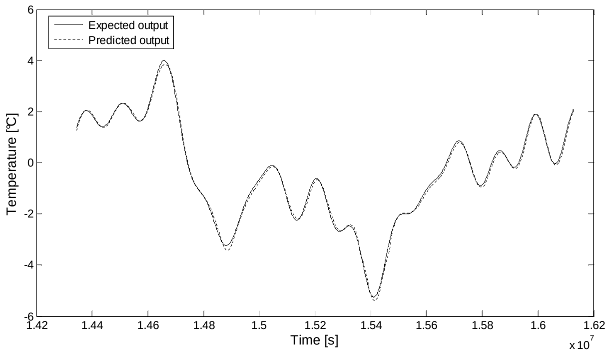

Fig. 11. Prediction of daily mean value temperature

predicted through the use of another Type-2 FLS. Figure 12 represents the reconstruction of the global daily temperature, after the modulation through the predicted envelop. Finally,

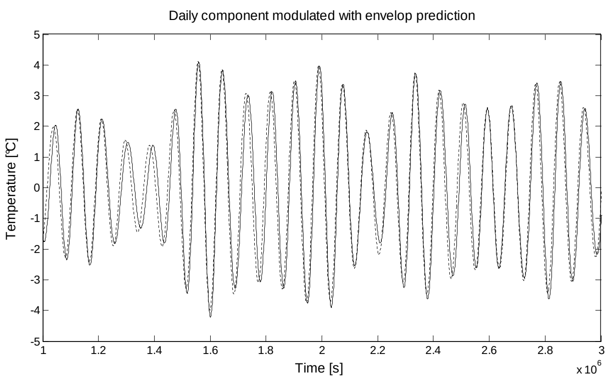

Fig. 12. Modulation of daily temperature

Fig. 13 shows the recomposition of the components, shown in Fig. 12 and 11, by means of (2), but without adding the biasing due to the extracted annual component.

VII. CONCLUSIONS

This paper presents a novel approach to forecast meteorological phenomena. It is based on the signal decomposition and on an architecture that uses a Type-2 FLS in order to predict the chaotic components.

Signal decomposition permits to focus the prediction only on chaotic components. This procedure allows to obtain long-term prediction bounded errors. Using Type-2 FLS is also very

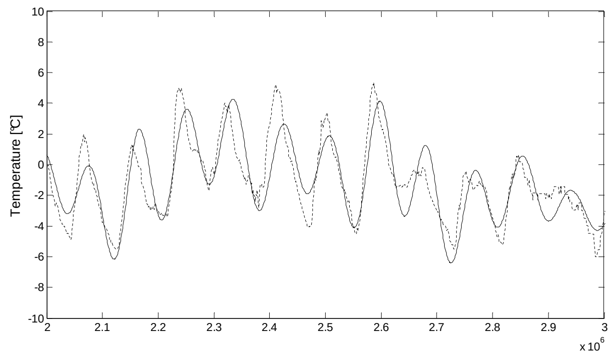

Fig. 13. Final temperature forecasting

important because this class of systems has shown small sensitivity to measurements uncertainty and noise. The whole system has been designed and simulated on historical meteorological data previously acquired.

First results show promising performance with respect to other methodologies.

The following step in research will be the implementation of the system in HW. It can be notice that, because the time between two consecutive measurements is equal to 900 s, the needed HW resources will be not expensive allowing to realize low-cost devices.

VIII. ACKNOWLEDGMENT

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