Predicting climate conditions using Internet-of-Things and artificial hydrocarbon networks

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Abstract— The prediction and understanding of environmental conditions is of great importance to prevent and analyze changes in environment, supporting meteorological based sectors, such as agriculture. In that sense, this paper presents an Internet of Things (IoT) system for predicting climate conditions, i.e. temperature, using artificial intelligence by means of a supervised learning method, the artificial hydrocarbon networks model. It allows predicting the temperature of remote locations using information from a web service comparing it with a field temperature sensor. Experimental results of the supervised learning model are presented in two modes: offline training to detect the suitable parameters of the model and testing to validate the model with new data retrieval from the web service. Preliminary results conclude that artificial hydrocarbon networks model predicts remote temperature with mean error of 0.05℃ in testing mode.

Keywords— artificial intelligence, DSA, EnOcean, Internet of Things, machine learning, predictive, Raspberry Pi, sensors, weather station, web service.

I. Introduction

The environmental conditions affect the daily life of many people around the world. The need of environmental information around the world is increasing as the technology of meteorological predictions increase and emerge new systems, and social media for exchange the information and the experiences of the citizens. The motivations and the grown of new software for weather report is increasing [1] and the software development helps to predict and understand the observations and the methods to prevent and predict the changes in the environment. With the increasing of the use of meteorological prediction data is necessary to improve new software that provides precise and actualized data [2]. These are used for control, monitoring the impact of the weather, and giving accuracy information for the public.

The meteorological system is based in a real-time sensor, that allows creating real data with information provided in the region [3-5]. With a right distribution of the sensors, it can be created a prediction based on the information acquired and the information in real time. New rising technologies help to keep in hand the needed information to anticipate to the weather and climate conditions.

The Internet of Things (IoT) is a technology that allows the connection with many devices to analyze multiple variables and control, automate and centralize systems with the analyzed data. This technology is applicable to devices like domotic control, smartphones, health systems, microprocessor devices, and many devices enhanced with communication systems [6]. With many protocols for communication and management, it allows the connection with sensors, cloud-based systems, control devices and monitoring [7]. The implementation of a weather system based on IoT gateway is based on an IoT platform or a web service system that monitories weather sensors, or a weather web service that can be monitored in any device connected to the IoT system. With a weather web service enlaced to the IoT system and multiple sensors, can be obtained a better accuracy data that predict and show weather statistics. Additionally, artificial intelligence, i.e. machine learning and data mining, have been used to enhance actions over IoT systems.

In that sense, this work proposes to apply artificial intelligence by means of a supervised learning method namely artificial hydrocarbon networks in order to predict the temperature in a remote location. This IoT system will use temperature information through a web service, and the temperature of a remote location will be predicted by the artificial hydrocarbon networks based module. For this work, a proof of concept was built to implement and validate the artificial hydrocarbon networks module. Two experiments were conducted. The first one considered training the intelligent module with information previously retrieved from the web service and a host in-site temperature sensor, aiming to find suitable parameters for the module. The second experiment was done in order to determine the effectiveness of the intelligent module for predicting the temperature of a remote location using only information acquired from the web service. Thus, the contribution of this work is the implementation of an intelligent module over the IoT system to predict climate conditions in remote locations using specifically artificial hydrocarbon networks method as the main intelligent system.

978-92-990075-8-7

The rest of the paper is organized as follows. Section II summarizes the prototype development of the IoT system. Section III describes the proposed intelligent prediction module using artificial hydrocarbon networks. Section IV presents experimental results and discussion about the proposal, and Section V concludes this work.

II. Prototype Development

The web service data and the temperature sensor were developed under DSA (Distributed Services Architecture) platform [8]. The purpose of the DS is to unify the different devices, services and application in real-time, structured and adaptable data model. We used a Raspberry Pi 3 [9] as a DSA Server to control the system using a distributed server link (DSLink) to enable data exchange with other connected nodes, as a weather web service and a protocol with EnOcean® [10].

We use the DGLux5® program in the DSA to create the design of the interface that will monitor the temperature of the web service and the sensor using the EnOcean® protocol. We used the conditional block for the logical part of the program, to display the different temperatures and save in a certain time the values in a database.

Figure 1 shows the logical blocks in the DGLux5® program to get the data of temperatures from the web service and the EnOcean® sensor. Figure 2 shows the architecture of the prototype development. The DSA obtain the temperatures from the web service connected to the cloud via the internet and the physical sensor using the EnOcean® protocol.

The information of the temperature was obtained by means of the implementation of a graphical interface, in the DGLux5® program, where it showed each one of the temperatures and it was possible to download a CSV file of each one of them, as shown in Figure 3.

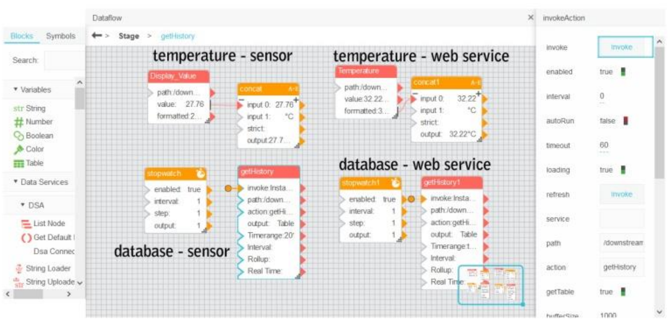

Fig. 1. Logic to get the data of temperature in the IoT system.

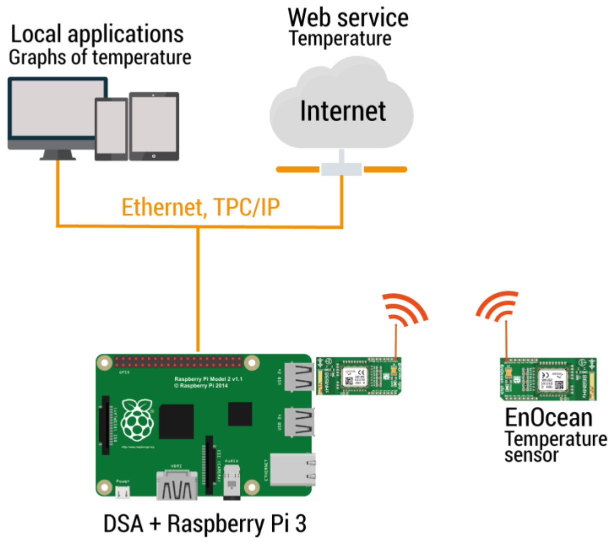

Fig. 2. Architecture of the IoT prototype system.

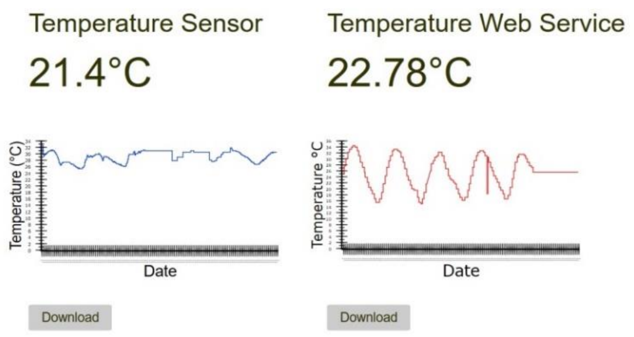

Fig. 3. Examples of temperature charts obtained from the IoT system.

III. Development of the Prediction Module

In order to develop an intelligent module that can predict climate changes through an IoT system, a supervised learning method is proposed to use. Particularly, this work only focuses on the prediction of in-site temperature using the IoT system presented in Section II. Following, an overview of artificial hydrocarbon networks method and the description of the module are presented.

A. Artificial Hydrocarbon Networks

In machine learning, artificial hydrocarbon networks (AHN) method is a supervised learning algorithm that is inspired on chemical organic molecules aiming to model and predict nonlinear relationships between input and output information, applied for robustness and partial interpretability of the model as well as treating with uncertain data [11]. In literature, there are reported several studies about prediction [11], classification [11,12], and other engineering applications such as intelligent control systems and image processing based on AHN [13].

Artificial hydrocarbon networks algorithm has basic units of information so-called molecules. These molecules locally model the behavior of a subset data, packaging information and functionality. The nonlinear relationship among molecules are then model using a compound. Lastly, different compounds can be mixed up in definite ratios resulting in a mixture [11]. Figure 4 shows a basic artificial hydrocarbon network.

As a supervised learning technique, AHN should be trained. The underlying algorithm that builds a new AHN-model is based on chemical heuristics mechanisms. These chemical mechanisms consider how to define relations between molecules and how to train them. In [11,12], a simple AHN-algorithm for building a model is reported, and it is adopted for this work. The input arguments required are: the number of molecules m and the learning rate parameter $0 < \eta < 1$.

B. Description of the Prediction Module

The temperature prediction module is based on artificial hydrocarbon networks, as shown in Fig. 5. As depicted, the intelligent module is divided in two steps.

The first one refers to the training step in which the artificial hydrocarbon networks method is built using the temperature measurements from both the web service and an in-site temperature sensor. Notice that the latter can be implemented as a mobile temperature sensor used only for a short period of time, then it can be moved elsewhere. This step considers to determine the best m and η parameters combination aiming to obtain the best AHN-model configuration.

Once the AHN-model is computed, the second step is used to predict the in-site temperature only using information retrieved from the web service. In that sense, the temperature from the web service is employed as input to the AHN-model, and the latter outputs a prediction of the in-site temperature.

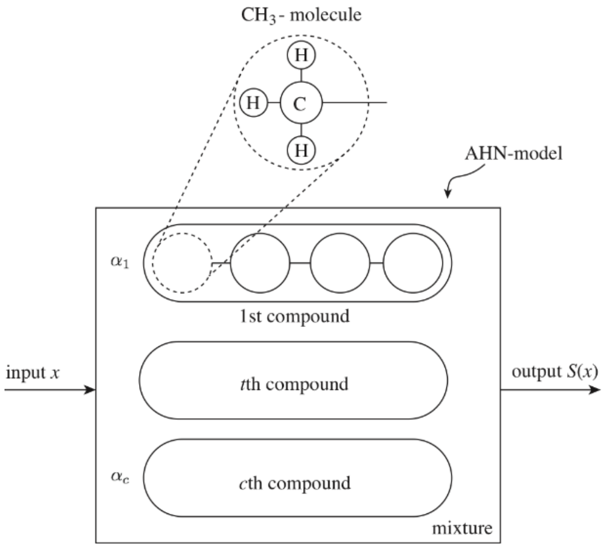

Fig. 4. Simple representation of an artificial hydrocarbon network model.

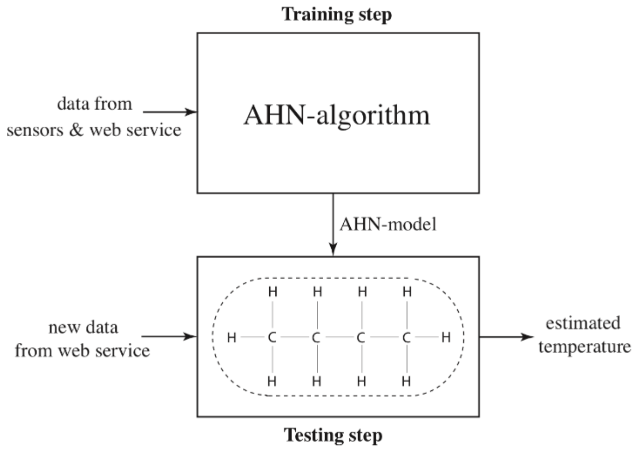

Fig. 5. AHN-based prediction module. Two steps are performed: the training step for building the AHN-model, and the testing step in which new data from web service is processed by the AHN-model to predict the in-site temperature.

IV. Experimental Results and Discussion

In this section, we built an artificial hydrocarbon networks model for the temperature prediction module, and we tested the performance of the module.

A. Training the AHN-Model

At training step, we collected 3,000 samples from both the temperature web service and the in-site temperature sensor. With this information, we used the temperature web service as the input and the temperature sensor as the output of the AHN-model. We also divided the samples in two subsets: a training data set (90% of the total) and a testing data set (10% of the total). Then, we ran a 3-times 10-fold cross-validation test to obtain the best AHN-model (i.e. compute the m and η parameters) that can predict in-site temperature. Table I shows the accuracy of the AHN-model at different number of molecules and learning rate parameters. As observed, the best combination of parameters was $m = 7$ and $\eta = 0.15$ with 92.43% in accuracy. To this end, this configuration was selected for the rest of the experiments.

Figure 6 shows a comparison between the output response of the AHN-model and the target output using the in-site temperature sensor. The maximum error obtained was 2.9℃ and the mean error was 0.55℃.

Table I. Accuracy of the AHN-model using different configurations of number of molecules and learning rate

m	$\eta = 0.05$	$\eta = 0.10$	$\eta = 0.15$
2	0.8906	0.8906	0.8906
3	0.9063	0.9034	0.9034
4	0.9195	0.9203	0.9151
5	0.9033	0.9012	0.9054
6	0.9137	0.9207	0.9123
7	0.9205	0.9187	**0.9243**
8	**0.9206**	0.9139	0.9177
9	0.9192	0.9160	0.9183
10	0.9202	**0.9219**	0.9169

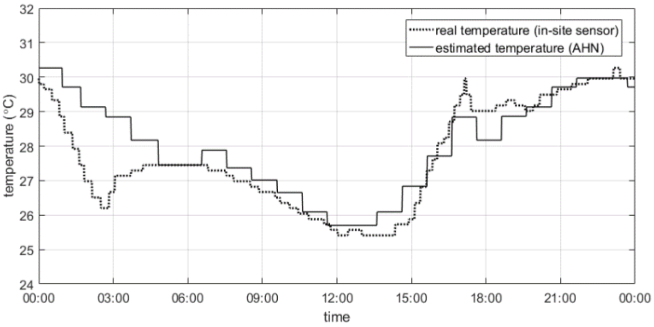

Fig. 6. Comparative time-series between the real in-site temperature and the estimated temperature using the AHN-model in training mode.

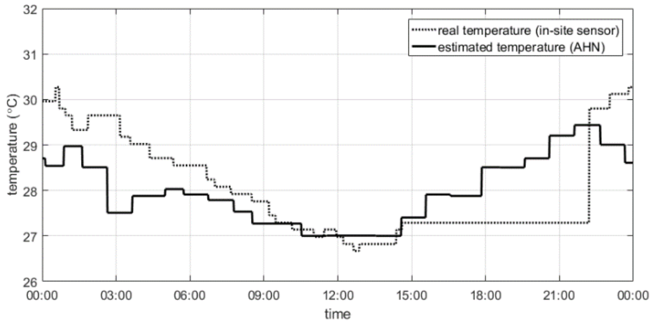

Fig. 7. Comparative time-series between the real in-site temperature and the estimated temperature using the AHN-model in testing mode.

B. Testing the AHN-Model

At testing step, we collected 1440 new samples (one-day per minute) from the web service and the in-site temperature sensor. It is important to notice that the AHN-model did not know about these samples before. For each temperature sample from the web service, it entered into the AHN-model based prediction module and the output was reported as the estimated in-site temperature. Figure 7 shows the comparison between the estimated temperature computed by the AHN-model and the real temperature from the in-site sensor. The maximum error obtained was 2.1℃ and the mean error was 0.05℃.

C. Discussion

From the results above, it can be seen that the AHN-model can predict the temperature in a remote location using the information from the web service with mean error of 0.05℃ in testing operation. In that sense, the proposed proof-of-concept of the IoT system improved with artificial intelligence for predicting climate conditions, has the following advantages: it estimates remote temperatures with high accuracy, it can integrate more sensors and the AHN-model can be retrained aiming to improve its performance, it can be used in remote locations without the need of in-site sensors, and the minimization of sensors reduces the maintenance of the whole system. However, several limitations have been identified in the first iteration of the IoT system design: it requires more data acquisition in order to perform better accuracy in the estimates, it needs a pre-training at each remote location, and it also needs retraining at different season periods because of the climate conditions.

V. Conclusions

In this work, we proposed an IoT system for predicting climate conditions remotely using artificial intelligence, i.e. artificial hydrocarbon networks method. Particularly, we proposed a proof-of-concept of the IoT system using an AHN-model as the temperature prediction module.

Two experiments were conducted in order to measure the performance of the proposed AHN-model. When training, the AHN-model obtained a maximum error of 2.9℃ in prediction and a mean error of 0.55℃. In testing, the AHN-model obtained a maximum error of 2.1℃ and a mean error of 0.05℃ in prediction. These results are very promising when dealing with forecasting in climate conditions.

Until now, there is strong evidence that the AHN-model can predict the temperature of remote locations using information from a web service. However, future work considers to retrieve more data information in order to determine the minimum amount of data required to adequately train the AHN-model. Also, other experiments increasing the number of sensors should be implemented. To this end, applications in precision agriculture and remote forecasting climate conditions will be taken into account for future research.

VI. References

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