PREDICTION OF MARS METEOROLOGICAL VARIABLES USING ARTIFICIAL NEURAL NETWORKS

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ABSTRACT

Weather forecasting is the task of determining future states of the atmosphere for a given location and time. The techniques to carry out the prediction range from deterministic approaches using complex fluid dynamics models to data-driven approaches using artificial intelligence. While the former is mainly focused on the creation of General Circulation Models, the later are starting to replace them in many situations for Earth's meteorology and astrophysics. Here, we develop an artificial neural network to perform Mars' weather forecasting using environmental measurements from the Vikings and Mars Science Laboratory missions. The methodology followed in of this study is a data-driven approach; we make use of computer science expertise which has been long applied to Earth, but not on Mars yet. To do so, we create an artificial neuronal network that predicts the meteorological conditions of the following day using the previous day as input. We show that temperature and pressure are among the most important variables, and that ANN can perform with a 0.5 to 1% accuracy in forecasting diurnal changes in the selected variables.

Keywords: ANN, Mars, Weather, Forecast, Curiosity

RESUMEN

La predicción meteorológica es la tarea de determinar los estados futuros de la atmósfera para un lugar y un momento determinados. Las técnicas para llevar a cabo la predicción van desde enfoques deterministas que utilizan complejos modelos de dinámica de fluidos hasta enfoques basados en datos que utilizan la inteligencia artificial. Mientras que los primeros se centran principalmente en la creación de Modelos de Circulación General, los segundos están empezando a sustituirlos en muchas situaciones de la meteorología y la astrofísica terrestre. En este trabajo desarrollamos modelos basados en redes neuronales artificiales para realizar la predicción meteorológica en Marte a partir de las mediciones ambientales obtenidas por las misiones Vikings y Mars Science Laboratory. La metodología seguida en este estudio es un enfoque basado en los datos que hace uso de los conocimientos informáticos que se han aplicado durante mucho tiempo en la Tierra, pero todavía no en Marte. Hemos diseñado y entrenado modelos neuronales que predicen condiciones meteorológicas de un día utilizando como entrada las variables del día anterior. En concreto hemos analizado la temperatura y la presión como variables más importantes, y hemos comprobado que una RNA puede conseguir una precisión de entre el 0,5 y el 1% en la predicción de los cambios diarios de las variables seleccionadas.

Palabras clave: Redes neruonales artificiales, Marte, Climatología, Predicción, Curiosity.

1. INTRODUCTION

Weather forecasting is the application of science and technology to predict the state of the atmosphere in a given location and time. A forecast generally requires collecting ground-based and orbital quantitative data on the current state of the atmosphere. These data are then processed by physical models with the aim of studying, understanding and determining the future state of the atmosphere. However, the lack of data, the complex nature of atmospheric phenomena, and the incomplete understanding of atmospheric patterns make the forecasting less reliable as the time range of the prediction increases. In order to predict specific features of the atmosphere, General Circulation Models (GCMs) include a wide range of variables to fine-tunning the results that are difficult to understand and work with.

To overcome those aspects, the use of artificial neural network (hereafter ANN) structures to predict the weather forecast is increasing, most of them pointing their research towards Earth.

ANN could be considered an accessory to the complex mathematical models used to predict weather forecasting, which in turn could be used to validate complex models. Data-driven approaches provide results faster and with greater simplicity, but does not give information on why the system has a particular behavior. On the other hand, fluid dynamic models help to understand the physics and chemistry of the situation but only after long and power-expensive computation times. Most of Mars' research up to date has been done using GCMs, and our aim with this study is to provide aid software system based on ANN for the studying of Mars' weather.

The first ANN structures were developed from known models of biological nervous systems and the human brain itself. The processing units, called artificial neurons, are simplified models of a biological neuron. These models were inspired by how a cell membrane of a neuron generates and propagates impulses [1].

The ANNs are part of the area known as intelligent systems or computational intelligence. Computational intelligence refers to the ability of a computer to learn a specific task from observation. The methods used are similar to the human's way of rationale, and it is able to produce control actions in an adaptive manner. In particular, ANNs allows the system to learn experiential data by operating as a biological one with a purely data-driven approach.

The artificial neurons used in ANNs are nonlinear, usually providing continuous outputs, and performing simple functions, such as gathering signals available on their inputs, assembling them according to their operational functions, and producing a response considering their innate activation functions

ANN' approaches have been used to solve real-world problems in many different fields. It has been proved to be a powerful technique for machine learning, successfully used for pattern recognition, statistical mapping or modelling. It has been applied successfully to different fields such as industrial processes, medical, business, or image recognition, and specifically or weather forecasting [2].

Forecasting thunderstorms is one of the most difficult tasks in weather prediction, due to their rather small spatial and temporal extension and the inherent nonlinearity of their dynamics and physics. In those situations, numerical models based on fluid physics may not provide reliable results or depend on many other unknown variables. Under those circumstances, AI techniques can prove useful in filling the knowledge gaps. For example, Mislan et al. [3] used ANNs to forecast monthly rainfall in Indonesia, and Litta et al. [4] developed different ANNs to forecast thunderstorms during premonsoon in Kolkata, India.

Besides the application to single phenomena, ANN can be used to model the environment of specific locations, such as Datta et al. [5] work on a complete statistical weather analysis of Austin, Texas. In the same line, Al-Kahlout et al. [6] forecasted forest fires using ANNs and meteorological data collected from the northeast region of Portugal, and Doğancan Ulutas et al. [7] used similar techniques for predicting air precipitation in Istanbul.

Approaches based on ANNs are becoming more frequent and expanding to other areas of meteorology. Recently, Lucas Olivera et al. [8] studied the hourly global solar radiation estimation, in Florencio Varela town, Buenos Aires using AI. Wu, J. et al. [9] developed a rainfall forecast model in coastal areas, developing a Back propagation ANN algorithm. Furthermore, instead of focusing on single events or small regional areas, approaches like Anochi et al. [10] show that it is possible to use ANN to forecast precipitation over large aras such as South America.

Albeit these studies are becoming mainstream, Mars' meteorology has not been researched extensively using ANN. Mars and its climate have been a subject of scientific curiosity for centuries, but only during the 17th century could the red planet be studied using Earth-based observations, with a close exploration not being possible until the beginning of the space race in the mid-1960s. Thanks to the development of space technology, we have some information about Mars meteorological parameters, as flyby and orbital spacecrafts have provided data from above while landers and rovers have measured atmospheric conditions directly from the ground. The actual knowledge of the Martian atmosphere comes from those observation data [11], and in this work, we propose a weather forecasting model of Mars using an ANN.

The advantage that ANNs have over other methods of weather forecasting is that they minimize the error by using several algorithms, providing a predicted value that is almost equal to the actual value. On the other hand, classical ANN techniques might fail in capturing isolated events such as dust devils, for which a large training set of events is not yet available. In Section 2, we review the most important physicochemical magnitudes driving Mars' meteorology and introduce the variables selected in our study, and in Section 3 we develop a set of ANNs for the Viking Landers (VL) 1 and 2, and for the Mars Science Laboratory, exploring the transportability of the networks for the VL1 and VL2. Finally, we summarize our findings in the conclusions.

2. WEATHER ON MARS

Mars' atmosphere shows many of the meteorological phenomena that occur on Earth, such as baroclinic disturbances, fronts, formation of CO_2 ice and water ice clouds, precipitation from CO_2 ice clouds, dust storms or dust devils. However, there are important differences with the Earth, such as its lower atmospheric density, completely different atmospheric composition, complex topography

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characterized by a dichotomy between both hemispheres, or the large variability of dust and water in the atmosphere.

The current Martian environment does not allow for the formation of pure liquid water on the surface due to the relatively cold temperatures, low atmospheric pressure, and modest amount of atmospheric water vapor [12]. This means that there is no significant latent heating in the Martian atmosphere due to water vapor, and, importantly, no ocean-continent disparity. This causes a major difference between the two planets: on Earth, the oceans act as large bodies with high thermal inertia and slow transport timescales, able to contribute to atmospheric forcing on long timescales and to suppress some of the atmosphere's variability, whereas on Mars there is no such 'coupling' between two systems. These differences impose restrictions on the direct use with Martian variables of ANN developed for the Earth. Since the ANN would have been trained to mimic our planet's atmosphere, the results would not be an accurate representation of the Martian atmosphere. Thus, in this work, we create, train and execute an ANN only with Mars' data without relying on previous ANN developed for the Earth.

One of the main meteorological parameters in any planet is the temperature of its surface and atmosphere. Since chemical reactions rates are modulated by the temperature, it is to be expected that it will play a major role in developing an ANN for Mars. Present Mars is much colder than the Earth (average air temperature is -63 °C) because, in addition to being located at a distance of 1.52 AU from the Sun, its thinner atmosphere results in a small radiative time constant and a weakening of greenhouse warming. The thin Martian atmosphere, together with the abovementioned absence of large volumes of liquid water and the low thermal inertia of the Martian soil, produces a large diurnal thermal amplitude that must be taken into account.

Nevertheless, of all the planets in the Solar System, Mars has the highest similarities with the Earth since it is composed of rock and high-density metals, and it rotates at approximately at the same rate and in the same direction as the Earth. Thus, the consideration of a data-driven approach to study the Martian atmosphere is not outlandish given the success of ANN applied to Earth meteorological studies. A Martian day, called "sol", lasts 24 hours and 39 minutes (a sol is 88775.245 seconds long), and its year lasts for 668.59 sols (approximately two Earth years), which is the reason why seasons on Mars are approximately twice as long as on Earth. The rotation axis of Mars is also very similar to that of Earth, with a 25° inclination (compared to 23.5° for the Earth), but with a much larger eccentricity of its orbit around the sun (0.093, whereas the Earth's is 0.017), producing a large difference in the maximum solar irradiation received in the northern hemisphere compared to the southern. As a result, the seasons are more extreme in the southern hemisphere: summer temperatures in the southern hemisphere can be up to 30 K warmer than their northern counterparts.

To account for this facts, in our study, we parametrize the orbital position of Mars using the Solar longitude (Ls), i.e., the angle that the planet Mars forms with the Sun measured from the spring equinox, where Ls is 0. Hence, Ls 90 corresponds to the summer solstice, Ls 180 corresponds to the autumn equinox and Ls 270 to the winter solstice, all of them relative to the northern hemisphere.

Mars has a predominantly (~95%) carbon dioxide atmosphere, part of which condenses onto the poles seasonally. The average global pressure on the surface is ~6 mbar (~1% of the Earth pressure). The global pressure gives us some information about the seasonal changes. Both polar caps are mainly composed of a permanent layer of water ice with a superficial CO_2 ice layer above it. One of the main differences between caps, in addition to its size, is the depth of that superficial CO2 ice layer, being ~1 m deep on the northern polar cap (which sublimates completely during the summer and condensates during winter), while the southern one, of about ~8 m deep, sublimates partially during the summer, and that is why the water ice layer underlying is not exposed at any time during the Martian year. The annual solar irradiation cycle produces then a CO_2 interchange between caps. About a third of the atmosphere is exchanged. This cycle, therefore, controls the overall atmospheric content of CO_2 and regulates the average daily pressure at a certain season.

Dust is ubiquitous in the Martian atmosphere, affecting the thermal, radiative and dynamical state of the atmosphere. It affects atmospheric heating mostly due to its significant absorption and scattering of short-wave (solar) radiation, and its relatively weaker absorption of long-wave radiation. Generally, dust has an anti-greenhouse effect on visible wavelengths, but opposite in the infrared. Therefore, an increase in the amount of atmospheric dust reduces the incoming solar flux on the surface, but increases the downwelling infrared flux. The net result is a decrease in temperature amplitude signal, increasing nighttime temperatures and decreasing daytime up to 20 K. The radiative effects of atmospheric dust are then very significant in determining the distribution of atmospheric heating. This temperatures alteration also has an effect on pressure and winds, which modify not only the atmospheric transport of dust but also its injection from the surface into the atmosphere, feeding then back the process. The dust season begins when the solar radiation incident in the southern hemisphere reaches important levels in the southern spring equinox (Ls 180) and ends when it descends into the southern autumn equinox (Ls 0). Global dust storms are one of the most unknown process of the Martian atmosphere. These storms, which to date are unpredictable, evolve from local dust storms in just a few sols.

Atmospheric mesoscale phenomena are classified within the space-time domain between short-lived microscale systems and long-term synoptic (global scale) systems. In practice, the division between microscale and mesoscale, and mesoscale and synoptic scale is quite diffuse. The revitalizing of Mars exploration in the early 1990s combined with the maturation of mesoscale modelling for Earth provided an ideal scenario for the application of the latter to the atmosphere of Mars. The use of mesoscale models has become an integral part of interpreting the data returned from Martian missions and providing constraints and bounds on environmental conditions

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in support of mission planning and operations. Mesoscale models are ideal tools for greatly minimize risk during entry, descent, and landing (hereafter EDL) phases. Slope winds, dust injection processes and atmospheric volatiles transport are the main mesoscale circulations that affect the atmospheric structure and dynamics on Mars. The annual evolution of Martian meteorological variables is nowadays well understood due to the exceptional performance of those models [13] and therefore the most valuable application of ANN models would be the fact-based determination of diurnal cycles of the parameters involved.

With all this in mind, this work aims to provide an accurate representation and forecast of the Martian atmosphere using as input variables the local true solar time, air temperature, pressure and orbit (solar longitude).

3. MARS PREDICTION

3.1 ANN models

The objective of this study is to develop an ANN to forecast the value of the main climate variables on Mars using in situ data. To do so, we rely solely on the empirical knowledge of the Martian atmosphere following a probabilistic approach using AANs without any Earth-training or modeling behind it. This methodology is complementary to numerical models, providing new tools to understand the processes of the Martian atmosphere. The indubitable advantage of a fluid dynamics model is that it provides information on the underlying physics of the process but with extreme complexity, while the data-driven approach provides results with greater simplicity but does not give information on why the system has a particular behavior.

Besides the forecasting of the variables, our approach can be used to fill the gaps in the event of a lack of measurements (e.g. adverse weather conditions or scheduled stops to adjust the software), or when validating other codes or new data, as the computational cost is much less than the required by Mesoscale Models for the Martian atmosphere.

Regarding the architecture of our model, Forward Feedback Propagation algorithms (FFBP) are selected for the neural network. The FFBP method for calculating network parameters uses an iterative Levenberg-Marquardt algorithm (LMA): from an initial set of parameters, LMA calculates step-by-step a final set of parameters that approximates the minimum criteria. Since the FFBP has several local minima and there is no evidence of the existence of a single global minimum, the output parameters depend on the choice of input parameters. In this sense, the backpropagation learning technique is the most effective technique for getting good results.

The neural feedback network is a non-parametric estimation of statistical models to extract non-linear relationships from the input data. The training algorithm consists of two phases (Rumelhart et al. [14]).

1. Forward phase: The free parameters of the networks are set and the input signal propagates through the network during this phase. It ends with the calculation of an error signal.

2. Backward phase: During this second phase, the error signal propagates backward through the network, hence the name of the algorithm. In this phase, adjustments are made to the free parameters of the network in order to minimize the error in the statistical sense. The backpropagation learning algorithm is easy to implement and computationally efficient.

In this article we use meteorological data obtained from the Viking Lander 1 (VL1), Viking Lander 2 (VL2) and Mars Science Laboratory (MSL) missions, which provide the longest and most comprehensive meteorological coverage of all the surface-based missions landed on Mars. We have created a database with the meteorological variables outlined above to develop an ANN for each of those missions. The following sections summarize the meteorological observations from these missions and describe the processing methodology applied to those observations. For a detailed study of all the meteorological packages sent to Mars, the reader is referred to Martínez et al. [15] which is the source of the datasets used in this study.

3.2 Viking Landers (VL1 and VL2)

The VL1 landed at 22.4°N in 1976 and operated for 2245 sols [i.e., ~3.3 Martian Years (MY), while the VL2 landed at 47.9°N later in that year and operated for 1281 sols. Here we use measurements taken by the Viking Meteorology Instrument System (VMIS) instrument and camera on-board VL1 and VL2. Specifically, we examine the near-surface air temperature (Ta) and atmospheric surface pressure (P) measured by VMIS, and the dust opacity (τ) at 670 nm retrieved from Sun images taken by the cameras.

VMIS nominally measured Ta in periods of 9 min at 0.25 or 0.125 Hz, 20 min at 0.5 Hz, or 39 min at 0.25 Hz, spaced 1.5 h throughout the sol, while P was measured once every 17 min (Hess et al., [16]). Later in the mission, the data acquisition frequency was significantly reduced. On another hand, the cameras took images of the Sun on 328 out of the first 920 sols of VL1, and on 250 out of the first 872 sols of VL2, Colburn et al. [17]

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We use VMIS measurements on sols with full diurnal coverage to calculate representative daily mean values of Ta and P at the VL1 and VL2 sites. For Ta, this strategy results in 2245 sols at the VL1 site and 1050 sols at the VL2 site, while for P it results in 1201 sols at the VL1 site and 830 sols at the VL2 site. Moreover, we use daily values of τ on each sol with available in-situ measurements.

The Neural Network Fitting Tool GUI nntool available in MATLAB 9.6.0 (R2019a) is used to carry out the analysis on the weather data using Artificial Feed-Forward Neural Network [ret (9.6.0.1335978 (R2019a) Update 8), The Math Works Inc., Product Help- Neural Network Toolbox)]. A two-layer feed-forward network with sigmoid hidden neurons and linear activation was selected to fit the weather problem. The network was train with Levenberg-Marquardt backpropagation algorithm. Five different network were train. All networks have 3 layers, input, hidden and output, the difference were the numbers of neurons into the hidden layer (5,10,15,20,25). To measure the accuracy of the ANN we use mean square error (MSE), which represents the average of the squares of the errors—that is, the average squared difference between the estimated values and the actual value. Also we used the coefficient of determination (R squared), which is the proportion of the variance in the dependent variable that is predictable from the independent variables. It measures how well observed values are replicated by the model; the closer to 1 the R is, the better the predicted result.

The approach followed with the datasets for each problem is the following. The dataset is split in two major groups, the first one that will be used to feed the neural network, the second group will be used as unknown set, to revalidate the results. The first set will be split in three subgroups, as usually is done working with neural networks, training, validation and test.

3.2.1. Viking Lander 1

We aim to develop and train two networks that can predict air temperature at the VL1 and VL2 sites for a particular sol using meteorological measurements of air temperature and pressure from the previous sol. For the VL1, we have a dataset of 1199 sols. This group will be split as mentioned before into two major groups, first 898 will be feed to the ANN and 301 sols as unknown set, used after the training of the network to revalidate the results. The first group (with 898 sols) are also split into 70% training set (628 samples), 15% validation samples (135 samples) and another 15% as testing (135 samples).

In our analysis, we choose to use the minimum number of variables to provide a reliable prediction. After testing a variety of parameters, the quantities selected as inputs are air temperature, pressure, and orbit (i.e. solar longitude). The results of the model for a different number of neurons are shown in Table 1. It can be seen that a low number of neurons is preferred to optimize the ANN and to obtain a better R squared with the unknown set.

Neurons	Training MSE	Training R^2	Validation MSE	Validation R^2	Testing MSE	Testing R^2	Unknown SET MSE	Unknown SET R^2
5	3.44529	0.966608	4.40219	0.960644	4.84870	0.955508	2.44669	0.961481
10	2.30202	0.976903	1.66325	0.984363	6.96840	0.944197	3.1750	0.955945
15	2.93266	0.971202	1.24373	0.989316	2.78628	0.975816	6.95638	0.889637
20	14.83581	0.867006	6.08082	0.940825	32.00879	0.760681	22.11552	0.721259
25	3.04406	0.971177	2.77620	0.966935	1.85559	0.985077	3.28129	0.954175

Table 1: ANN results for VL1

Figure 1 figure shows the temperature in K as a function of the Solar Latitude. The red line indicates the in situ observation of the temperature while the blue curve shows the result of the ANN using the reserved Unknown set (of 301 sols) as input. It can be seen that, in general, the ANN provides an accurate estimation of the temperature with less than 0.5% of discrepancy with the actual observation. Specific orbital positions show a greater discrepancy up to 1% (~2K), which indicates that external parameters not accounted for in our model might be in play. A more complex ANN including some of the parameters described above could provide better results for fine-tunning the model at specific times (for example between sols 80 and 120).

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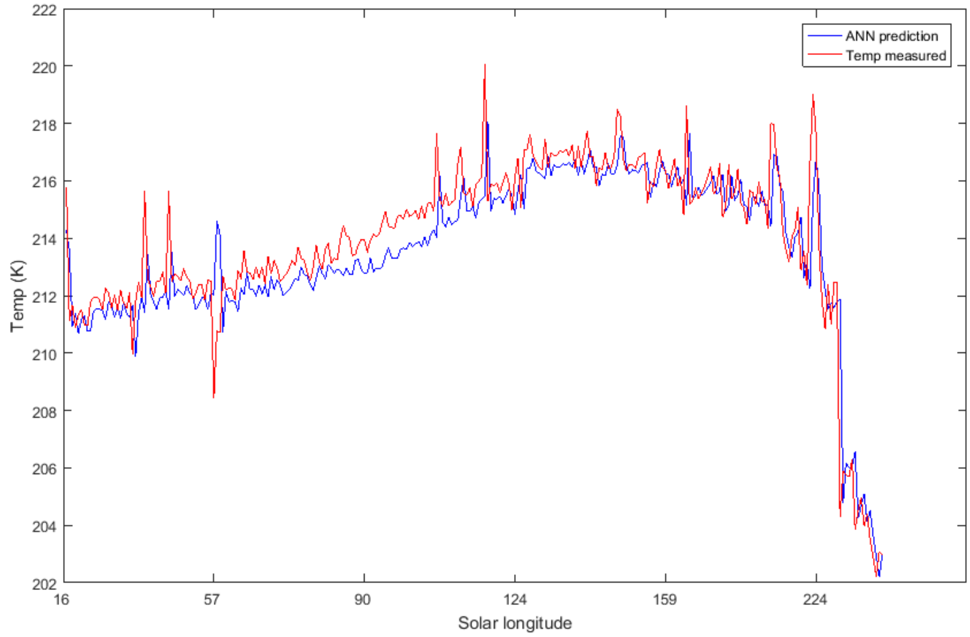

Fig. 1: Neural network VL1 predicting temperature.

3.2.2. Viking Lander 2

In this case, we split the data set of 828 sols from VL2 into two major groups, first 611 as training data for the ANN. Those data are also split into 70% training set (427 samples), 15% validation samples (92 samples) and another 15% as testing (92 samples). Similarly, we reserve the last 217 sols as unknown set used afterwards to revalidate the results.

As in the case of the VL1, the variables selected from the set are the air temperature, pressure, and orbit (solar longitude). It highlights that both the testing and unknown set R values are higher than those obtained for VL1 regardless the number of neurons used. Unlike the VL1 where the unknown set R value showed a decrease until 25 neurons just to increase afterwards at the expense of higher computational power, the VL2 model is monotonic in its decrease and thus the 5 neurons are optimal for our study.

Neurons		Training MSE	Training R^2	Validation MSE	Validation R^2	Testing MSE	Testing R^2		Unknown SET MSE	Unknown SET R^2
5		4.69236	0.994222	4.48763	0.994835	4.84966	0.994087		12.55534	0.986074
10		5.41114	0.993482	4.09797	0.995534	5.73779	0.993976		11.09182	0.984617
15		4.07411	0.994936	5.09595	0.993738	3.27621	0.996392		11.74683	0.984825
20		4.29535	0.994663	45.33154	0.943427	4.63965	0.994735		11.62279	0.983780
25		2.96438	0.996354	5.91211	0.992325	3.66295	0.995878		14.50912	0.980573

Table 2: ANN results for VL2

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We present the results of our analysis of VL2 in Figure 2, plotting the reserved result of the ANN with the Unknown set as input (blue line) along with the in situ observation (red line). In contrast to the VL1, the use of just three variables for the prediction of the temperature overestimates the observation for the majority of the dataset. In certain orbital positions, the difference between the ANN and the observations is up to 3%, and the diurnal variability is predicted in much less amplitude. These facts imply that VL2 meteorology could be driven by other variables which do not play a significant role for VL1 such as opacity, wind or ground temperature.

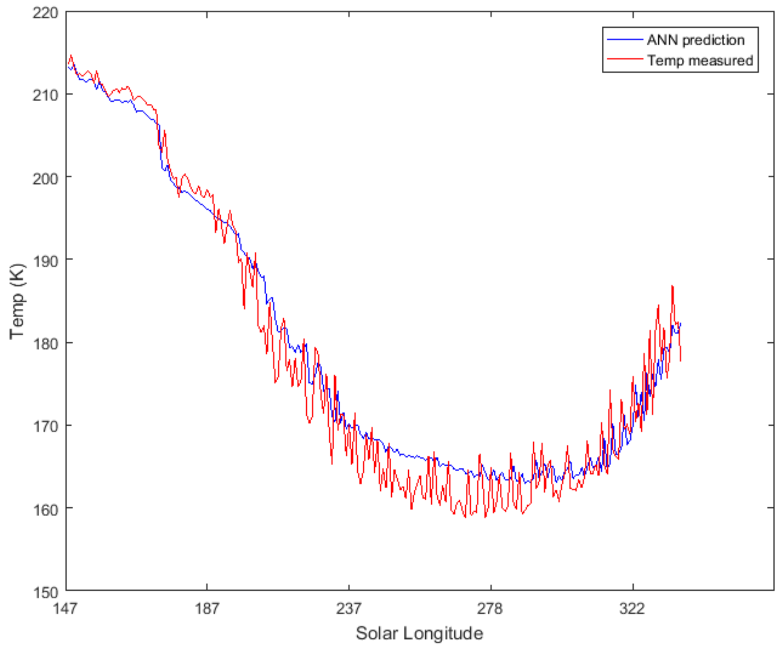

Fig. 2: Neural network VL2 predicting temperature.

3.2.3. Transportability of ANN

Having selected the neural networks for both Viking Landers, the question of portability arose. As discussed above, it would be unfeasible to apply an ANN trained with Earth data to study the Martian atmosphere, but, could we use the ANN of VL1 with the data obtained from VL2, and vice versa? In order to validate the idea, first we provide the VL2 data to the ANN obtained for the VL1 (Figure 3), and then we use the VL2 ANN with VL1 (Figure 4) to observe the differences).

In the first case (VL1 ANN on data from VL2), we obtain a MSE of 64.57 and a R of 0.98316, with discrepancies up to 10% in some cases, overestimating the observed temperature in basically all situations. As discussed above, the meteorological conditions during some orbital positions for VL2 seem to be determined for variables other than temperature, pressure and orbital position. Therefore, attempting to forecast the temperature using only those variables, and being those variables exogenous to the location, results in unreliable predictions at some times.

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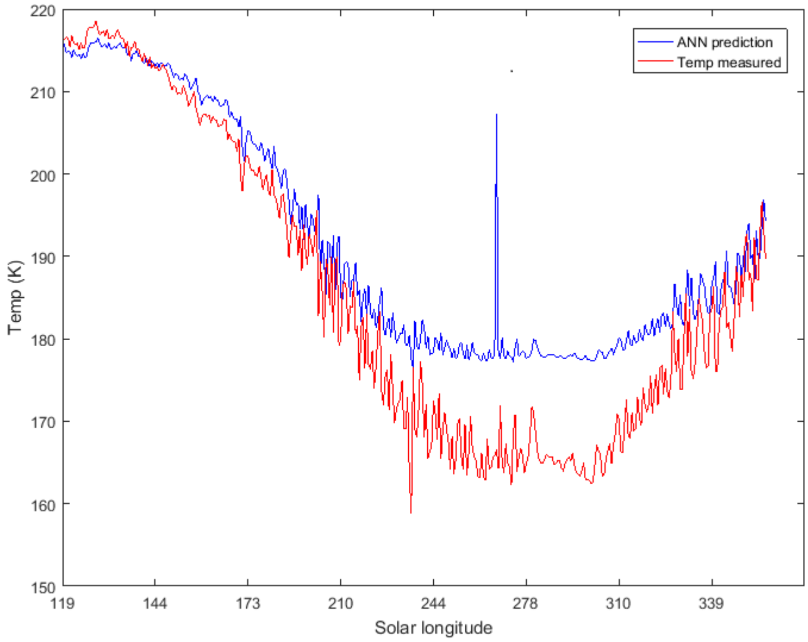

Fig. 3: Neural network VL1 predicting VL2.

The results of using VL2 ANN on data from VL1 are more interesting. In this case, the value of the MSE was 256.19 and R squared of 0.91714. As it can be seen in Figure 4, the forecast (blue line) starts underestimating the observations and after approximately 50 sols it flips with respect to them (red line). When the observations start to decrease drastically around 200 sols, the prediction falls as well, capturing the trend correctly. However, the differences between the real behavior and the predicted values disagree excessively. These differences are explained as follows; the ANN is trained to output an absolute value for the temperature in K depending on the variation of the input parameters. The training set used for this ANN had small variations in the input parameters, and thus the introduction of larger variabilities results in larger predictions.

These two examples show that ANN are useful tools for Martian forecasting but the specific architecture and weights depend strongly on the location. Should anyone try to extrapolate results from one location to another, the results would become unreliable. Even though the Martian atmosphere is regarded as simple and predictable when compared with our own atmosphere, the oversimplification of the methodologies used for forecasting would provide inaccurate results.

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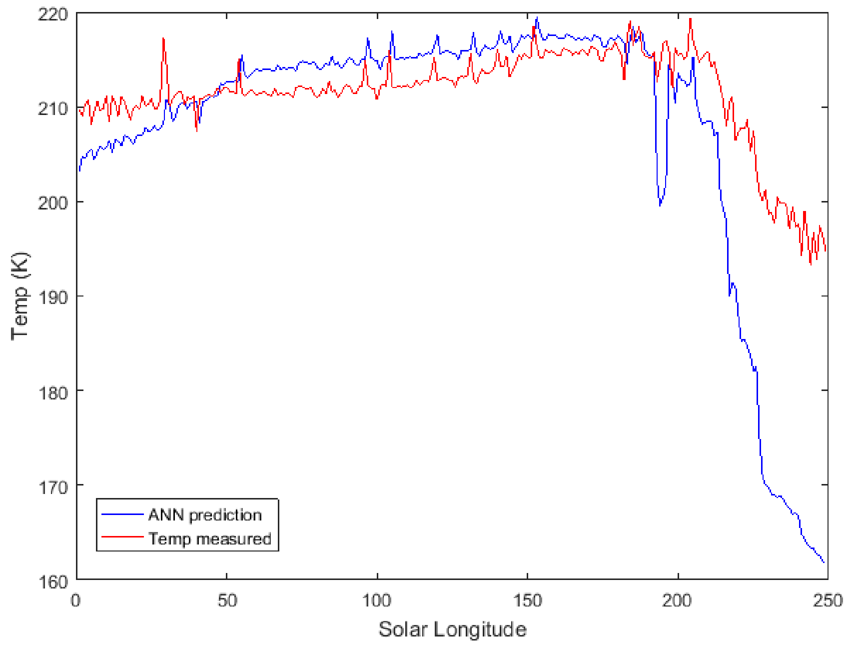

Fig. 4: Neural network VL2 predicting VL1

We observe on both swaps a really good R squared with a large error (>30%). The result of the experiment shows us that there is no direct transportation from one region to other, and the recommendation would be to develop a new network to solve the problem.

3.3 Mars Science Laboratory (MSL) Mission

In this section, we aim to develop a more complex ANN for the meteorologic variability of the location of the Curiosity rover. The MSL landed in Gale Crater (4.59S, 137.44E) in August 2012 and as of October 2020, it has been operating for more than 2900 sols. Here we analyze measurements taken by the Rover Environmental Monitoring Station (REMS; Gómez-Elvira et al. [18]) and Mastcam instruments on board MSL during the first 2000 sols of the mission. In particular, we examine P, Ta, ground temperature (Tg), and relative humidity (RH) measured by REMS, along with τ at 880 nm retrieved from the Mastcam instrument.

REMS nominal sampling strategy consists of measurements taken at 1Hz during the first 5 minutes of each hour, with additional full hour sample periods at 1Hz to cover every hour of the sol over a period of a few sols. On another hand, Mastcam retrieves τ values with a typical cadence of once every six or seven sols.

Given REMS nominal measuring strategy, here we use REMS measurements taken during the first 5 minutes of every hour to calculate hourly and daily averages of Ta, Tg and P during the first 2000 sols of the mission. Moreover, we use daily values of τ on each sol with available measurements.

The objective is to create and train a network that can predict individual weather components (temperature, pressure, humidity etc.) for a particular sol, given the values of the variables from the previous sol. Here we report only the temperature and pressure because the main focus is to prove the ANN approach is valid for weather forecasting on Mars, but other variables can be obtained with the same methodology with similar accuracy. The temperature is arguably the most important parameter in Mars' atmosphere since it is one of the main drivers of atmospheric chemistry and the determining factor in solar cell temperatures [19].

The input data set consists of 1637 days corresponding to two Martian years and a half (2.45 years). Each day consists of 24 measurements. Out of the 1637 samples, 1227 samples were used to develop the network and 410 samples reserved for a late revalidation, as unknown set. From the 1227 samples, 70% of them are used as training data for the neural network and are randomly selected by nntol; 15% samples are validation data which measure the generalization of the network by feeding it with data it has not seen before; the remaining 15% of the samples are the test data and give an independent measure of the performance of the ANN in terms of MSE (Mean squared error).

For the prediction of the temperature and the pressure, the quantities selected as inputs are: local true solar time, air temperature,

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pressure, and orbit (solar longitude) of each sol. Those variables were the selected set, the minimum amount of variables which explained 99% of the values, resulting in a high accuracy ANN. Including more variables just added complexity and did not help to the model.

Table 3 shows the results with different number of neurons. It highlights once again that a higher number of neurons is not translated into a more accurate prediction. Thus, we select 5 as an optimum number of neurons for creating the ANN. It is also remarkable that the testing MSE is higher for 5 neurons but the MSE for the unknown set is lower for this number of neurons. This shows the importance of splitting the complete dataset into parts and reserve a sufficient sample for validation.

Neurons	Training MSE	Training R^2	Validation MSE	Validation R^2	Testing MSE	Testing R^2		Unknown SET MSE	Unknown SET R^2
5	10.84709	0.999944	10.47866	0.999946	10.95767	0.999944		7.83929	0.990657
10	9.447385	0.999951	9.53764	0.999951	9.41453	0.999951		8.77725	0.990357
15	9.12516	0.999953	9.39396	0.999952	9.44041	0.999951		8.97762	0.989863
20	8.98696	0.999954	8.82985	0.999954	8.95814	0.999954		9.92400	0.989374
25	8.72240	0.999955	8.97163	0.999954	9.03682	0.999954		10.97657	0.989269

Table 3: NNs results for predicting the temperature at Curiosity's location.

Figure 5 shows the air temperature prediction versus air temperature measured for 10 sols from the second data set (unknown data set). As it can be seen, the margin of error is less than 0.5% in most situations, with the higher differences found when the air temperature is minimum overnight.

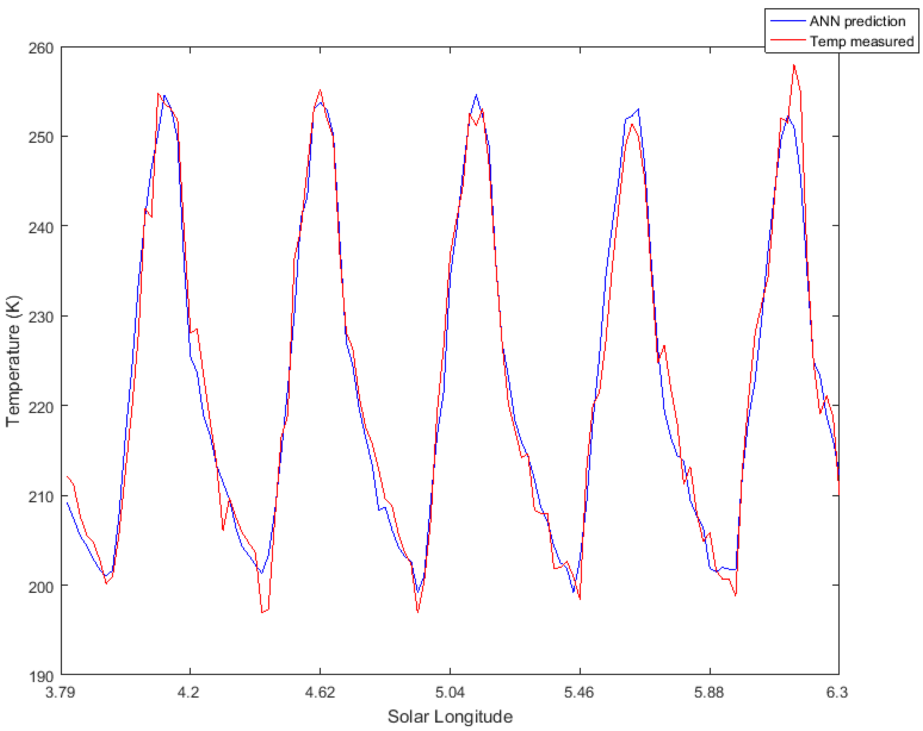

Fig. 5: Measured air temperature and its prediction.

Similarly, Figure 6 shows the pressure prediction versus pressure measured for 5 sols from the second data set (unknown data

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set). This time the error is generally less than 0.2%, and the minimum overnight is captured accurately. Since the other variables are completely deterministic parameters (local true solar time and solar longitude), we conclude that the stochasticity found for the air temperature in the minimum overnight comes from external factors not analyzed with our network. These variations could be produced by unpredictable downslope winds which could cool down the sensor momentarily. Those downslope through the crater rims winds could be either dynamically-induced windstorms related to gravity wave activity, or thermodynamically -induced katabatic winds (Rafkin et al. [20]). Unfortunately, the wind sensors of the REMS instrument do not provide data with sufficient accuracy to include it as a variable in our analysis.

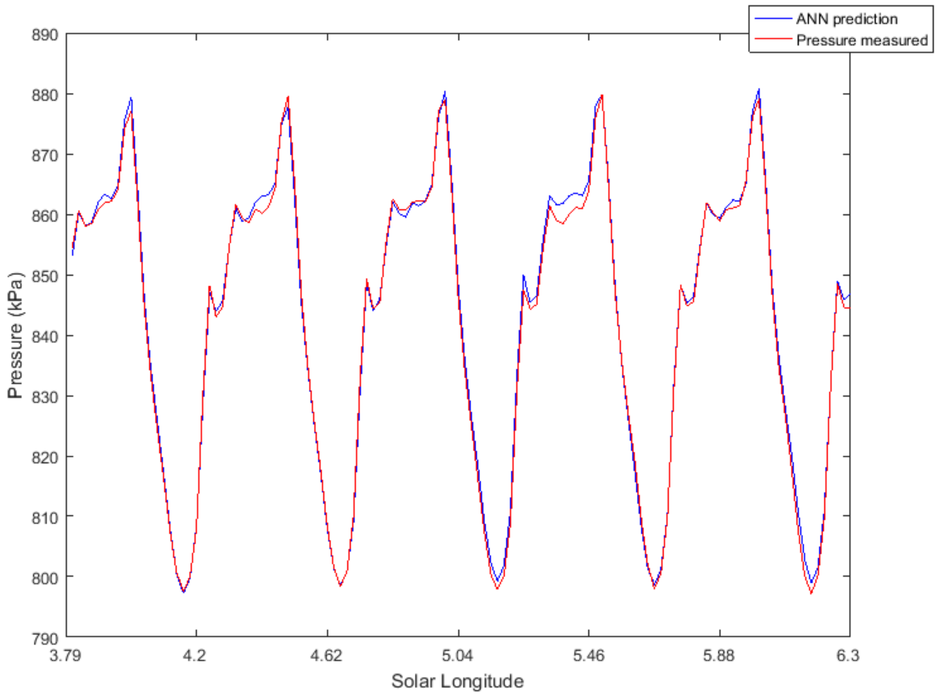

Fig. 6: Measured pressure and its prediction.

4. CONCLUSIONS

The analysis presented in this work prove that the application of artificial neural networks to forecast Martian meteorological variables is a valid approach, useful to complement current models, gain insights on Mars' atmosphere, and analyze data from the future meteorological stations on Mars.

We show that the prediction for the three locations studied, i.e. VL1, VL2 and MSL, provide results with very low margins of error. However, when a network trained for one location is intended to be used with data from a different area, the errors increase dramatically.

In our work, we aim to develop the minimum working ANN which would provide realistic forecasting for the meteorological data spending the minimum amount of time and computer resources. This approach is useful to fill gaps in the datasets and also to study the origin of diurnal or hourly fluctuations around the predicted values. As an example, we focus on the random changes of air temperature overnight and show that the pressure is not responsible for those variations, hypothesizing the reason of those changes being nocturnal turbulence driven by downslope winds. Should the capacity of the processors sent to Mars continue to increase, it will be feasible to include these algorithms to process the data in situ and optimize the measurements to provide the highest amount of information.

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