Abstract— In this paper a totally different approach, namely, a neural network based technique, is introduced to address the rainfall estimation problem. Radar data and satellite observations are used to demonstrate the neural network based rainfall estimation procedure. We have created a network for identifying the raining cloud. The target output of the neural network corresponding to radar data. The Multi-layer perceptron was created using seven spectral parameters that were calculated from MSG thermal infrared satellite images in order to identify rain and no rain pixels. The results obtained show the neural network performs very well.

Keywords—rainfall estimation; Radar data; satellite observations; neural network.

I. INTRODUCTION

Precipitation can be considered the most crucial link between the atmosphere and the surface in weather and climate processes. Quantitative precipitation estimates at high spatial and temporal resolution are of increasing importance for water resource management.

The traditional ways made so far to collect rainfall data remain insufficient. In addition, despite the efforts of the scientific community that tries to extend the operational meteorological radar networks, large areas remain uncovered where information about the occurrence and the intensity of precipitation are missing.

Meteorological satellites are the only instruments capable to provide large amounts of rainfall measurements in remote areas where data are difficult or impossible to collect from the ground. Therefore, Satellite precipitation estimates are widely used to estimate global rainfall on different timescales for climate studies ([1]; [2]; [3]; [4]; [5]). Programs such as Global Precipitation Climate Project (GPCP), Climate Prediction Center using Goes Precipitation Index (CPC), Estimation of Precipitation using Satellite (EPSAT) ([6]; [7]). Tropical Applications in Meteorology using Satellite data, Global Atmosphere Research Program (GARP) have also been developed and applied to estimate precipitation.

Techniques researching the relationship between thermal infrared and intensity of precipitation have been widely used [8] or Cold Cloud Durations (CCD). They are based on the assumption that the clouds with tops colder in the infrared produce more precipitation. Despite this large number of techniques, however, they are mainly applied to estimate rainfall accumulation during longer periods of time to obtain satisfactory results.

In this context, the rainfall estimation problem can be viewed as a complex function approximation problem. Neural networks are well suited for this problem, and the theoretical basis is provided by the universal function approximation theorem. Recent research has shown that neural network techniques can be used successfully for ground rainfall estimation from radars for classification, data retrieval, forecasting ([9];[10];[11]), downscaling , parameterization and problems related to the quality of the data series.

Neural networks (NNs) may present several advantages with respect to conventional techniques ([12];[13]). Their main feature is the ability to map input–output data to any degree of non linearity. It is well known that the NNs exhibit the capability to learn and to represent highly nonlinear functional and to be quite robust to noise . Moreover, if properly designed, an NN can be suitable to represent dynamical random processes such as the temporal evolution of a rain field.

The basic aim of this paper is to exploit the potential of a methodology based on neural networks to retrieve the rainfall pattern, having at disposal SEVIRI passive sensor data. This methodology uses a neural network to identify the raining pixels. The neural network includes two stages, namely, 1) the training and validation stage and 2) the application stage. In the training stage, the neural network learns the potential relationship between the SEVIRI information and the radar measurements from a training dataset. When a SEVIRI information set is applied to the neural network, the network yields a rainfall-rate estimate as output. This output is compared with the radar measurement, and if their difference or the error is propagated back to adjust the parameters of the network. This learning process is continued until the network converges. Once the training process is complete, a relationship between the SEVIRI information and the radar
measurements is established and the network is ready for operation. When a SEVIRI information vector subsequently is applied to the network, it yields a rainfall-rate estimate.

II. PRESENTATION OF STUDY REGION AND DATA
Algeria is located on the South shore of the Mediterranean region; it is bordered on the East by Tunisia and Libya, on the South by Niger and Mali, South-West by Mauritania and Western Sahara and West by Morocco. The spatial distribution of precipitation is characterized by a very marked North-South gradient and a very low East-West gradient. The rainy season extends from October to March, with maximum rainfall occurring during November-December. In the north, the climate is Mediterranean transit, marked by seasonal oscillations. The average annual rainfall is estimated at about 600 mm. The minimum rainfall is recorded in the southern regions. It is about 50 mm while the maximum is observed in the Djurdjura massif located in Kabylia and the massif of Edough located a little farther east, where it exceeds 1500 mm. The study area is located in the north of Algeria; it is depicted in Fig.1.

The National Office of Meteorology (Office National de Météorologie, ONM) located in Algiers, which manages the meteorological data is equipped with:
- A receiving station of SEVIRI data : two channels visible bands VIS0.6, VIS0.8, a near infrared channel NIR1.6, eight channels in the infrared and water vapor IR3.9, WV6.2, WV7.3, IR8.7, IR9.7, IR10.8, IR12.0 and IR13.4, and a visible channel HRV broadband covering only a part of the Earth disc.
- A chain of acquisition and digitization of meteorological radar data.

This study makes use of coincident and collocated 15-min observation datasets of SEVIRI infrared channels and radar measurements for the area of north Algeria (Fig. 1). These data collected during the period from November 2006 to April 2007 were used as rainfall information to train the models of neural network. SEVIRI datasets were used to develop the rain area delineation models and include channels in the thermal infrared. They have a 15-min temporal sampling and a spatial resolution of 3x3 km2 at sub-satellite point, reaching 4x5 km2 at the area of study. While Radar images are collected at a temporal resolution of fifteen minutes and a spatial resolution of 1km² in a format of 512x512 pixels. Each pixel is coded on four bits. The physical parameter of the radar is the reflectivity factor, denoted Z and expressed in \( \text{mm}^2 \text{m}^{-1} \). The conversion of reflectivity factor Z into precipitation intensity \( R(\text{mm} / \text{h}) \) is obtained by using equation 4 and can also be converted into dBZ:

\[
Z = 300. R^{1.5}
\]

Because of discrepancies between the SEVIRI data and radar data, due to differences in observation time, parallax errors and collocation errors, the comparison of these types of data may be hampered. To reduce the imbalances mentioned above and find a better correlation, we performed a repositioning to SEVIRI data to coincide spatially with radar data. The resolution is 4x5km in the study region and is assumed constant due to low overlapped area observed by both sensors. Therefore, each SEVIRI pixel is collocated with 4x5 radar pixels.

The time lag between the radar and the satellite is about 3 min. This small time difference does not require synchronization between the two data types.

III. METHODOLOGY
In our application, we have created network for estimating amount of precipitation. The target outputs of the neural network correspond to radar data. A neural network learns the input–output relationship through the training process. The learning process in a neural network is an interactive procedure in which its connection weights are adapted through the presentation of a set of input–output training example pairs.

A. Application
The neural network was created using seven spectral parameters that were calculated from MSG thermal infrared satellite images in order to identify rain and no rain pixels. It was created with three layers (input, hidden, and output) that consist of 7 input neurons, 8 neurons in the hidden layer and 2 output neurons in the output layer that represent the 2 classes corresponding to radar data. The multilayer perceptrons algorithm is selected from other statistical methods for the following reasons: 1) The MLP algorithm does not require any a priori knowledge of the statistical distribution of the data 2) The MLP can model non linear functions and can be trained to perform accurate generalization when inserting new unknown
Cloudy systems observed from passive radiometers are potentially precipitating if its effective particle radius $r_e$ and its optical thickness $\tau$ are large enough \[14\]. This assumption is based on the fact that large particles may fall against the updraft field in a cloud of vertical extension, which promotes the growth of these particles. Works were published showing that the effective droplet radius exceeding 15 $\mu$m become sensitive to gravity and fall as precipitation \[15\]. Therefore, the knowledge of information about the microphysical properties of clouds offers the possibility of an improved identification of raining clouds.

The effective droplet radius $r_e$ and the optical thickness $\tau$ of clouds both represented by a single parameter referred to as Cloud Water Path (CWP) are directly related to the probability that a cloud is precipitating. The CWP represents the amount of water vertically integrated in the cloud and depends on the diameter of raindrops and the thickness of the cloud formed by these drops. The relationship is given by the following equation \[2\]:

$$
CWP = \frac{2}{3} \rho \tau r_e^2
$$

Where $\rho$ (g/m$^3$) is the density of water in the clouds.

The combination of the channel \(\text{IR3.7}\) with the channel \(\text{IR11}\) was already used to extract information about microphysical and optical cloud properties. \[14\] attempted to relate the brightness temperature difference $\Delta T_{\text{IR3.7:IR11}}$ of satellite TRMM to effective particle radius and to cloud optical thickness. They showed that for a cloud top temperature higher than 260K, precipitation is obtained when the $\Delta T_{\text{IR3.7:IR11}}$ is in the interval $1\,\text{K}$, $4\,\text{K}$. Values lower than the interval are obtained when the cloud is optically thick with small effective particle radius. Values higher than the interval correspond to a semi-transparent cloud. These two situations correspond to a non-raining cloud. \[2\] used the channel \(\text{IR3.9}\) and the channel \(\text{IR10.8}\) of SEVIRI radiometer on ice clouds and water clouds. They get the same conclusions as. Indeed, a precipitating cloud indicates mean values for $\Delta T_{\text{IR3.9:IR10.8}}$.

In general, $\Delta T_{\text{IR3.9:WV7.3}}$ should show similar characteristics as $\Delta T_{\text{IR3.9:IR10.8}}$. Because of the diminishing effect of the water vapour absorption and emission in mid- to low tropospheric levels on the brightness temperature (BT) in the channel \(\text{WV7.3}\), $\Delta T_{\text{IR3.9:WV7.3}}$ should be generally higher than $\Delta T_{\text{IR3.9:IR10.8}}$.

Therefore, $\Delta T_{\text{IR3.9:WV7.3}}$ is expected to provide additional information about the CWP. For thin clouds with small or large particles, respectively (small or medium CWP), $T_{\text{IR3.9}}$ is larger than $T_{\text{WV7.3}}$ and $\Delta T_{\text{IR3.9:WV7.3}}$ reaches the highest values. Large particles together with a high optical thickness (high CWP) result in medium to high difference values, which are lower than for optically thin clouds. Thick clouds with small particles (medium CWP) lead to small $\Delta T_{\text{IR3.9:WV7.3}}$.

Therefore, we use suitable combinations of brightness temperature differences ($\Delta T$) between the thermal bands of MSG SEVIRI to infer qualitative information on CWP ($\Delta T_{\text{IR3.9:WV7.3}}$ and $\Delta T_{\text{IR3.9:IR10.8}}$) \[3\]; \[16\]. Let CWP as a function of $\Delta T_{\text{IR3.9:IR10.8}}$ versus $\Delta T_{\text{IR3.9:WV7.3}}$ is given in the figure 2.

![Fig.2. Cloud water path as a function of $\Delta T_{\text{IR3.9:IR10.8}}$ versus $\Delta T_{\text{IR3.9:WV7.3}}$](image-url)
A.2. Information from IR10.8

Brightness temperature $T_{IR10.8}$ is an indication of the vertical extent of the cloud because, in general, brightness temperature of the system depends on the cloud-top height [17].

A.2.1. Information from $\Delta T_{IR10.8-IR12.1}$

The brightness temperature difference $\Delta T_{IR10.8-IR12.1}$ being a good indicator of the cloud optical thickness, is very effective in discriminating optically thick cumuliform clouds from optically thin cirrus clouds [17]. Optically thick cumulus type cloud shows the smaller $\Delta T_{IR10.8-IR12.1}$ due to their black-body characteristics, while optically thin cirrus cloud shows the larger $\Delta T_{IR10.8-IR12.1}$ due to the differential absorption characteristics of ice crystals between the two channels. It is expected that optically thick and deep convective clouds are associated with rain. Even though the split window technique is very effective in detecting and removing optically thin cirrus clouds with no precipitation, it sometimes incorrectly assigns optically thick clouds like cumulonimbus in place of optically thin clouds.

A.2.2. Information from $\Delta T_{WV7.3-IR12.0}$ and $\Delta T_{WV6.2-IR10.8}$

Test $\Delta T_{WV6.2-IR10.8}$ is effective in distinguishing between high-level and low-level/mid-level clouds. The 6.2-µm channel is dominated by atmospheric water vapor absorption. Low-level clouds produce temperatures at the 6.2-µm channel lower than their actual cloud top temperatures due to the absorption from water vapor above them. In contrast, their cloud-top temperatures at the 10.8-µm window channel are representative of actual cloud-top temperature since the atmosphere is transparent to this wavelength. As a result, $\Delta T_{WV6.2-IR10.8}$ tends to be very negative in sign for low-level clouds. In contrast, upper level thick clouds (being above most of this vapor and having absorption similar for both wavelengths due to ice crystals) produce temperatures at the 6.2-µm channel close to their actual cloud-top temperatures. In this case, $\Delta T_{WV6.2-IR10.8}$ usually takes very small negative values. Semitransparent ice clouds, such as cirrus, constitute an exception to this rule since their differential transmission cause larger negative differences. Positive differences may occur when water vapor is present in the stratosphere above the cloud top, which is a sign of convective cloud tops as opposed to mere cirrus clouds.

In general, $\Delta T_{WV7.3-IR12.0}$ should show similar characteristics as $\Delta T_{WV6.2-IR10.8}$.

A.2.3. Information from $\Delta T_{IR8.7-IR10.8}$

The brightness temperature difference $\Delta T_{IR8.7-IR10.8}$ can be utilized to gain information about the cloud phase. The imaginary (absorption) component of the index of refraction, which is a direct indicator of absorption/emission strength, differs for ice and water at these two wavelengths. More specifically, the difference in water particle absorption is small between the two wavelengths, but very large for ice particles. Radiative transfer simulations show that for ice clouds, $\Delta T_{IR8.7-IR10.8}$ tends to be positive in sign, whereas for low-level water clouds, $\Delta T_{IR8.7-IR10.8}$ tends to be small negative. This simple parameter is adequate for classifying the cloud phase as either “ice” or “water”. We can expect ice cloud phase to be more associated with rain.

A.3. Use of MLP1 to identify raining pixel

The seven parameters presented previously will be used as input data, and information about rain from meteorological radar as output data (fig.3). The MPL rain delineation algorithms were trained using spectral parameters that were computed from SEVIRI dataset during the period November 2006 to April 2007.

![Fig.3. Structure of Multilayer Perceptron rain area delineation algorithm (MLP) that combines seven spectral parameters from SEVIRI satellite images](image)

IV. AINFALL IDENTIFICATION RESULTS AND PERFORMANCE EVALUATION

Models are validated against independent rainy days during November 2009 to April 2010, not used for training the rain area delineation algorithms. The evaluation was performed by comparison with instantaneous ground-based radar data collocated with SEVIRI data. The aim is to evaluate the potential of MLP algorithm in the identification of precipitation. The observation scenes made by the radar and satellite at a rhythm of 15 minutes are 15880, most of which are non-raining situations.
In order to evaluate MLP algorithm relative to the technique (ECST, Enhanced Convective Stratiform Technique), the validation scenes were also classified by the ECST (Thies et al, 2008).

The results were calculated at scale of pixel of SEVIRI images, in collocation with radar data. Each observation gives about 6500 pair of pixels in co-coincidences. The evaluation parameters are determined from Table (1) and are given as follows:

<table>
<thead>
<tr>
<th>Identified by satellite method</th>
<th>Raining</th>
<th>No raining</th>
<th>Total</th>
</tr>
</thead>
<tbody>
<tr>
<td>Raining</td>
<td>A</td>
<td>B</td>
<td>a+b</td>
</tr>
<tr>
<td>No raining</td>
<td>C</td>
<td>D</td>
<td>c+d</td>
</tr>
<tr>
<td>Total</td>
<td>a+c</td>
<td>b+d</td>
<td>a+b+c+d=n</td>
</tr>
</tbody>
</table>

Table.1. Overview of the combinations in a contingency table

Where a, b, c and d were values from a contingency table (Table1).

- The Probability Of Detection (POD) measures the fraction of observed events that were correctly identified:

\[ POD = \frac{a}{a+c} \]  (3)

The optimal value of the POD is: 1.

- The Probability Of False Detection (POFD) indicates the fraction of pixels incorrectly identified by the satellite method.

\[ POFD = \frac{b}{b+d} \]  (4)

The optimal value of POFD is: 0.

- The False Alarm Ratio FAR measures the fraction of estimated events that were actually not events:

\[ FAR = \frac{b}{a+b} \]  (5)

Its optimal value is: 0.

- The Frequency BIAS index (Bias):

\[ Bias = \frac{a+b}{a+c} \]  (6)

The optimal value of the Bias is: 1. It measures the overestimation or underestimation of the method. A Bias greater than 1 indicates an overestimation, while a bias lower than 1 indicates an underestimation.

- The Critical Success Index (CSI) measures the fraction of observed and/or estimated events that were correctly diagnosed:

\[ CSI = \frac{a}{a+b+c} \]  (7)

The optimal value of CSI is: 1.

- The Percentage of Corrects (PC) is the percentage of correct estimations:

\[ PC = \frac{a+d}{n} \]  (8)

The optimal value of PC is: 1.

The statistical results of the verification for MLP1 and ECST are given in TABLE 2

<table>
<thead>
<tr>
<th></th>
<th>POD</th>
<th>POFD</th>
<th>FAR</th>
<th>Bias</th>
<th>Bias</th>
<th>PC</th>
</tr>
</thead>
<tbody>
<tr>
<td>ECST</td>
<td>0.64</td>
<td>0.06</td>
<td>0.29</td>
<td>0.85</td>
<td>0.58</td>
<td>0.93</td>
</tr>
<tr>
<td>MLP</td>
<td>0.76</td>
<td>0.04</td>
<td>0.23</td>
<td>0.96</td>
<td>0.69</td>
<td>0.96</td>
</tr>
<tr>
<td>Optimal values</td>
<td>1</td>
<td>0</td>
<td>0</td>
<td>1</td>
<td>1</td>
<td>1</td>
</tr>
</tbody>
</table>

Table.2. Results of evaluation parameters.

We observe a net difference for the detection of raining clouds between the two methods. 76% of raining pixels observed by radar are also identified by the MPL algorithm against 64% for the ECST method. This difference is due to the incorporation of the information about the optical thickness and the phase of clouds provided by the spectral parameters from SEVIRI data, that has enhanced the identification. The FAR parameter indicates 0.23% of pixels that are misclassified by MLP against 0.23% for the ECST technique. Values of POFD are very low due to the high number of non-precipitating scenes that are correctly identified by both methods. This also gives high values for PC. These parameters depend not only on the scenes of precipitation correctly identified but on all situations, raining or non-raining. In contrast, the CSI parameter depends on raining scenes which shows a good performance for the MLP algorithm with CSI (0.66). Compared to ECST (CSI 0.53), this indicates an improvement for the MLP. Bias parameter shows that both techniques underestimate the precipitation. The Bias for MLP is 0.96 while the Bias for the ECST is 0.85.

All these evaluation results show the good performance for the MLP. The joint combination of information about physical and thermodynamic cloud properties derived from different channels of SEVIRI has better identified the precipitating clouds. In contrast, for scenes classified by the ECST, the results show that the identification of raining clouds still unsatisfactory in the mid-latitudes.
V. CONCLUSION

A neural network technique to estimate rainfall based on SEVIRI multiparameters is introduced in this paper. The neural network directly maps the SEVIRI observations to Radar rainfall from the ground. The training and testing of multilayer perceptions based on SEVIRI and Radar data from different days during the our experiment demonstrate that the neural network has the ability to generate potentially more accurate and robust rainfall estimates than the existing IR retrieval techniques. In addition, the neural network estimates of rainfall using both and are better than the neural network estimates based on alone, thereby indicating the contribution of measurement for rainfall estimation in a neural network context.

Indeed, the use of the first network of neurons has eliminated the non-precipitating clouds to focus on the precipitating clouds to find the best synaptic weights of the second network of neurons. Altogether, the evaluation study shows an encouraging performance of the developed technique. Implementation of the neural network offers the great potential for area-wide rainfall detection and its quantification in a high spatial and temporal resolution.

A further improvement in the estimate performance of an NN algorithm can be investigated if a wider set of input/output patterns, which are representative of different meteorological and geographical situations, is provided to the network during the training phase. Another possible way to optimize the estimate capability of an NN-based system is to use multisensory information at a higher sampling rate, using the MSG data from different multispectral channels.

Because of the existing demand for such area-wide rainfall data, the introduced technique and underlying conceptual model merit further research. This is particularly true for the for the development of an improved assignment of the rainfall rate to the detected rain area.

REFERENCES


