Abstract— In this paper, we investigate the performance of MLP neural networks in terms of ECG signal prediction. In spite of quasi-periodic ECG signal from a healthy person, there are distortions in electrocardiographic data for a patient. Therefore, there is no precise mathematical model for prediction. Here, we have exploited neural networks that are capable of complicated nonlinear mapping. In this way, 2 second of a recorded ECG signal is employed to predict duration of 20 second in advance. Our simulations show that PSO algorithm can find the neural network with minimum MSE and the accuracy of the predicted ECG signal is 94%.

Index Terms— Electrocardiogram, MLP artificial neural network, PSO algorithm, predict, accuracy.

I. INTRODUCTION

Electrocardiogram is an important tool for providing information about heart activity [1]. The first electrocardiographic (ECG) signal was obtained in 1895 by Willem Einthoven. Though the basic principles of those systems are still applied, many advances have been made over the years. The schematic of a single heartbeat in ECG signal is indicated in Figure 1 [2]. Since the normal kind of signal belonged to a healthy person is according to a known structure, changing and disturbing in any important parameters represent a heart disease. As a result, physicians try to diagnose different heart disorders by analyzing ECG signals. For example, Gilberto Sierra in 1997 performed a frequency analysis for the purpose of cardiac death forecasting [3] and M. Arvaneh in 2009 predicted paroxysmal atrial fibrillation by dynamic modeling of the PR interval [4].

II. METHOD

A. Multilayer Perceptron (Mlp) Network

One of the most popular neural networks is feed forward MLP network by back propagation training algorithm which is shown in figure 2. Although, the number of neurons in the input and output layers is determined by the user requirements, the number of layers and also the number of neurons in each hidden layer are optimized by trial and error procedure.

It can be seen from figure 2 that the output is expressed by:

\[ y_0(t) = \sum_{j=1}^{m} w_{jk} \varphi \left[ \sum_{i=1}^{n} w_{ij} v_i(t) + b_j \right]; \quad 1 \leq k \leq m \]  

Where \( w_{ij} \) is the connection weight from i-th input to the j-th hidden node, \( w_{jk} \) represents the connection weight between hidden and output layer, \( v_i(t) \) is i-th data of the input vector, \( b_j \) denotes the bias in j-th hidden node and \( \varphi(\cdot) \) is the activation function [6]. The activation function of neurons in hidden layers is normally selected of Sigmoidal type with the following equation:

\[ \varphi(x) = \frac{1}{1+e^{x}} \]  

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Fig. 2 Three Layers Of A Feed Forward Neural Network Which Illustrates A MLPN [7]

B. Particle Swarm Optimization Algorithm

The Particle Swarm Optimization is an evolutionary computation developed by James Kennedy and Russell Eberhart [8] in 1995. The basic PSO model consists of a swarm of m particles moving about in a D-dimensional real value search space [9].

PSO is initialized with a population of random solutions (particles). Each particle has two states, the current position p and the current velocity v. The velocity and position of each particle is updated using following formulas [10],

\[
\begin{align*}
V_i & = w \cdot V_{i-1} + c_1 \cdot r_1 \cdot (P_i - p_i) + c_2 \cdot r_2 \cdot (P_g - p_i) \\
p_i & = p_{i-1} + V_i
\end{align*}
\]

Where, \(P_i\) is the best position of ith particle experienced, \(P_g\) is the best position swarm experienced, \(w\) is called the inertial weight, \(c_1\) and \(c_2\) are the acceleration constants, \(r_1\) and \(r_2\) are the random numbers uniformly generated from \([0, 1]\). A limit velocity called \(V_{max}\) is imposed on particles. If calculated velocity of a particle exceeds this value, it will be reset to the maximum velocity.

III. PREDICTION OF ECG SIGNALS

In this work artificial neural network has been exploited to estimate \([(n+1)th, (n+2)th, ..., (n+m)th]\) samples from \(n\) previous ones. Then the estimated samples are returned back to the input layer for prediction of \(m\) next samples started from \(n+m+1\).

In the applied networks, input layer consists of 50 neurons which are equal to the number of samples in 2 second of the original signals. The number of hidden nodes is selected based on PSO algorithm and the number of output nodes is set to be 50 which are corresponding to the number of predicted samples. A schematic of the applied networks in this paper has been shown in figure 3.

Here, we have employed a database consists of 50 signals taken from 50 persons in the intensive care unit (ICU) that 10% of them were healthy and 90% of them were patient. First, All signals have been noise canceled using wavelet transformation. Then, all data were normalized to lie between 0 and 1. After that they have been divided into three datasets named as: training (60% of all data), test (20% of all data) and validation (20% of all data). Figure 4 shows some instances of denoised signals from the mentioned database.

IV. RESULTS

To verify the performance of the ECG prediction systems, the difference between the output and target values is calculated using Mean Square Error (MSE). The MSE parameter is expressed as:

\[
mse = \frac{1}{n} \sum_i (y_d(t_i) - y_o(t_i))^2
\]

Where \(y_o(t_i)\) is the ith network output, \(y_d(t_i)\) is the ith desired output and \(n\) is equal to the number of predicted samples.

In neural networks we aim to achieve the minimum mean square errors. Usually, neural networks are optimized by trial and error procedure. Therefore, in this paper the best neural network is selected through PSO algorithm. Figure 5 shows the choice of best neural network flowchart.
In the flowchart, particles are number of MLP hidden layer neurons and position is MSE of network.

MSE and regression of five different networks and the best network are shown in Table 1. As shown in this table, the architecture of best network is 50-26-50 with 0.00798381 MSE and 94% accuracy.

One predicted ECG signal for healthy person is shown in Figures 6. These results obtained from the best MLP neural network (50-26-50) and another network with 50-41-50 architecture. In this procedure, 20 seconds of signal are predicted in 0.5 second.

<table>
<thead>
<tr>
<th>Number of Neurons in Hidden Layer</th>
<th>MSE</th>
<th>Regression</th>
</tr>
</thead>
<tbody>
<tr>
<td>19</td>
<td>0.01073576</td>
<td>0.78</td>
</tr>
<tr>
<td>24</td>
<td>0.00839905</td>
<td>0.90</td>
</tr>
<tr>
<td>26</td>
<td>0.00798381</td>
<td>0.94</td>
</tr>
<tr>
<td>37</td>
<td>0.00817835</td>
<td>0.92</td>
</tr>
<tr>
<td>41</td>
<td>0.00916798</td>
<td>0.84</td>
</tr>
<tr>
<td>44</td>
<td>0.00855093</td>
<td>0.82</td>
</tr>
</tbody>
</table>

V. CONCLUSION

In this paper, PSO algorithm is proposed and applied to selecting of MLP neural network architecture. This algorithm compares the MSE of different networks and it chooses the neural network with minimum MSE. Results show that PSO algorithm can be used as an alternative way in selecting network architecture. Therefore, the best neural network architecture is 50-26-50 to prediction of ECG signals. The accuracy of the predicted ECG signal is 94%.

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