Prediction of J-V Characteristic of Organic Solar Cells Using ANFIS Model

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***Abstract* — In this work, we have used ANFIS to predict *J-V* characteristic of bulk heterojection organic solar cells under different ratios of P3HT/PC_{70}BM concentration. Three types of membership function were used namely: Gbellmf, Trapmf and Pimf. The accuracy of the quality prediction were evaluated by different statistical parameters (R^2, *RMSE* and *MARE*). It is found that all used functions give results close to those obtained experimentally. However, Gbellmf seem to have the best quality of prediction highlighted by the calculated statistical parameters for this case.**

From the obtained results, we can say that regarding the flexibility of the developed model, its use in the area of organic solar cells is very suitable.

Keywords—ANFIS, Organic Solar Cells, Prediction, Bulk heterojection.

I. Introduction

In recent years the source of renewable energy is organic photovoltaic (OPV) and in the last two decades it has attracted a lot of attention. Actually, this type of solar cells check the terms of the task in terms of low- cost, flexibility, large area, and lightweight [1].

Most of organic solar cells use an active layer; it is a blend of a conjugated polymer and a fullerene such as bulk heterojunction (BHJ). These blends constructed of an electron-donor and an electron-acceptor respectively, and are blended together. The donor has the highest occupied molecular orbital (HOMO) and the acceptor has the lowest unoccupied molecular orbital (LUMO). Usually the fullerene [6,6]-phenyl C_{71}-butyric acid methyl ester (PC_{70}BM) and poly(3-hexylithiophene) (P3HT) are the most widely used materials as acceptor and donor, respectively mixed in a solution that forms two interpenetrating networks [2-3].

The morphology of the BHJ layer has a very large effect on the performance of the solar cell. Careful optimization of the processing conditions (concentration, solvent, temperature, donor/acceptor ratio) of the layers is crucial to obtain the best cells.

The blend (P3HT/PC_{70}BM) is one of the most intensively studied active material systems for bulk heterojunction solar cells due to the efficient dissociation of excitants and high carrier mobility [3].

The almost published results worldwide on the organic solar cells are carried out experimentally. However a small amount of papers introduce the predicting and modeling aspect. Tessarallo et *al.* [4] have used an easy and fast capacity measurement to predict the thermal stability of organic solar cells. In another work, Dong et al. [5] introduce Artificial Neural Network (ANN) in prediction of solar cells.

In this work we will introduce a new intelligent technique based on the Adaptive Neuro-Fuzzy Inference System (ANFIS) to predict the J-V characteristic of organic solar cells according to the different concentrations of the PC_{70}BM. The obtained results are compared with the experimental values and prediction quality is evaluated using the Root mean Square Error (RMSE).

II. Overview on the Organic Solar Cells

Organic solar cells can be classified by different criterions. The type of BHJ is the one of these criterions. The BHJ is formed by a mixture of two or more polymeric materials with different electronic affinities and ionization potential. The polymeric materials should be diluted in a common solvent. The resulting mixture is deposited by spin coating to obtain a thin film with dominions of both materials in nanometric scale. The interpenetrated regions must be continues to transport the charge carriers [6].

Performance of bulk heterojection depends in type of blend in active layer and ratios of the acceptor (PC_{70}BM in our case) in wt %. The morphology of the active layer can also be modified by post-deposition methods like thermal or solvent annealing. In [7] the investigated work highlights that the crystalline structure of the P3HT/PCBM has been affected by its concentration in solvent during the active solution preparation leading to the alteration of the PV performances. Supriyanto et *al.* [8] have found also that different mass concentration of P3HT/PCBM influences the efficiency of organic solar cells.

III. Structure of ANFIS Model

The Adaptive Neuro-Fuzzy Inference System (ANFIS), was introduced by Jang [9]. It contains the flexible structure of neural network and utilize a feed forward network to finalize the fuzzy rules which can perform better on assigned task can find the relation between the input and output data through hybrid learning to determine the optimal distribution of membership functions. This system is composed of five layers and is used to construct this inference system. As it can be seen in figure 1, each layer contains several nodes described by the node function. Adaptive nodes denoted by squares, represent the parameter sets that are adjustable in these nodes, whereas fixed nodes denoted by circles, represent the parameter sets that are fixed in the system. The output data from the nodes in the previous layers will be the input in the present layer. To illustrate the procedures of an ANFIS, for simplicity, we consider only two inputs *x* and *y* and one output in this system. The framework of ANFIS is shown in Fig. 1, and the node function in each layer is described below.

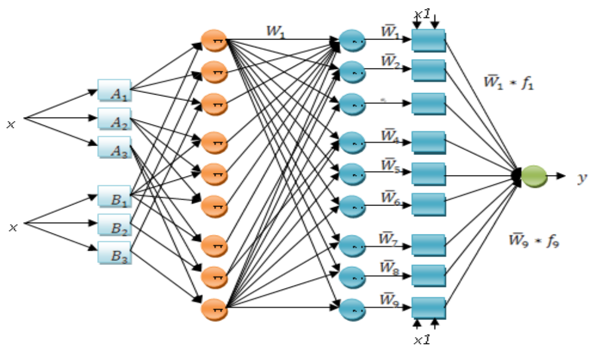

Fig.1. Architecture of the used ANFIS.

We can describe the different layers of the ANFIS system as follow:

Layer 1: The first layer is the fuzzy layer that converts the inputs into a fuzzy set by means of membership functions (MFs). It contains adaptive nodes with node functions described as:

$$O_{1,i} = \mu_{A_i}(x) \qquad for \qquad i=1,2 \qquad (1)$$

$$O_{1,i} = \mu_{Bi-2}(x) \quad for \qquad i=3,4 \qquad (2)$$

Where *x* and *y* are the input node *i*, *A* and *B* are the linguistic labels associated with this node, $\mu(A)$ and $\mu(B)$ are the membership function (MFs).

Layer 2: Every node in this layer is a fixed node, marked by a circle and labeled by Π, with the node function to be multiplied by input signals to serve as output signal.

$$O_{2,i} = w_i = \mu_{Ai}(x).\mu_{Bi-2}(y), \quad for \quad i=1,2 \qquad (3)$$

Where the $O_{2,i}$ is the output of Layer 2. The output signal w_i represents the firing strength of the rule.

Layer 3: Every node in this layer is considered as a fixed node, marked by a circle and labeled by *N*, with node function to normalize the firing strength by computing the ratio of the i_{th} node firing strength to sum of all rules' firing strength.

$$O_{3,i} = \overline{w} = w_i/(w_1 + w_2), \quad for \qquad i=1,2 \qquad (4)$$

Where the $O_{3,i}$ is the output of Layer 3. The quantity $\overline{w}$ is known as the normalized firing strength.

Layer 4: Every node in this layer is an adjustable node, marked by a square, with node function as following:

$$O_{4,i} = \overline{w}_i . f_i, \qquad for \qquad i=1,2 \qquad (5)$$

Where f_1 and f_2 are the fuzzy [IF-THEN] rules as follows:

- Rule 1 : IF *x* is A_1 and *y* is B_1, THEN $f_1 = p_1\, x + q_1\, y + r_1$
- Rule 2 : IF *x* is A_2 and *y* is B_2, THEN $f_2 = p_2\, x + q_2\, y + r_2$

Where p_i, q_i and r_i are the parameters set, referred to as the consequent parameters.

Layer 5: Every node in this layer is a fixed node, marked also by a circle and labeled by **Σ**, with node function to calculate the overall output by:

$$O_{(5,i)} = \Sigma_i\, w_i.f_i = (\Sigma_i\, w_i\, f_i) / w_i = f_{out} = Overall\ output \qquad (6)$$

IV. Results and Discussions

The proposed ANFIS model is used to predict *J-V* characteristic of organic solar cell, and the obtained results will be analyzed in this section. The aim of the prediction task is to predict the effect of the acceptor concentration. The presented characteristics in figure 2 [6] have been carried out at different ratios of $P3HT/PC_{70}BM$ blends. The used ratios are denoted by S1 (1:0.5), S2 (1:0.8), S3 (1:1.0) S4 (1:1.2) and S5 (1:1.5) corresponding at weight percent (wt%) of $PC_{70}BM$. The used ANFIS model has two inputs: the first is the applied voltage and the second is the wt% of the $PC_{70}BM$, and one output corresponding to the current density

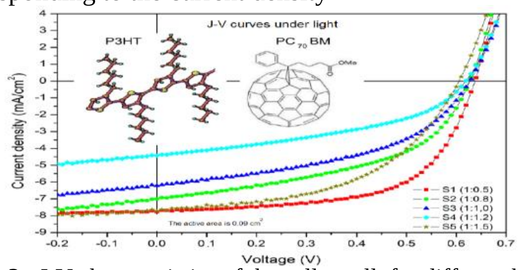

Fig.2. J-V characteristics of the sollar cell for different blend ratios of $P3HT:PC_{70}BM$ [6].

The Adaptive Neuro-Fuzyy Inference System model uses SUGENO model. First, with FIS editor window a new FIS is created with the two input variables and one output variable, the same FIS is set for training. The variable data are loaded from the experimental values for training the FIS. This FIS is generated using the grid partition and the same has been further edited to change number of Membership Functions (MFs). We have used [5 5] MFs having three different shapes: Gbellmf, Trapmf and Pimf. After generating the FIS it has been trained using hybrid optimization method.

The generated model has been used to predict the *J-V* characteristic for values of the current density and applied voltage out of the trained interval. We have reached values of 0.8V for applied voltage corresponding to values up than 8mA/cm² for the current density.

The experimental and modeled *J–V* characteristics of different blend layers (P3HT/PC_{70}BM) are plotted in figures 3.a, 3.b, 3.c, 3.d and 3.e. The experimental results highlights that *J-V* characteristics depends on the weight concentration of the fullerene blend layers (P3HT/PC70BM). From the variation of *J-V* characteristic, we can deduce different important parameters such as PCE, FF, factor ideality, R_s and R_{sh}. These factors are directly related to the performance of the solar cell and hence will be influenced by the concentration of the acceptor and the donor.

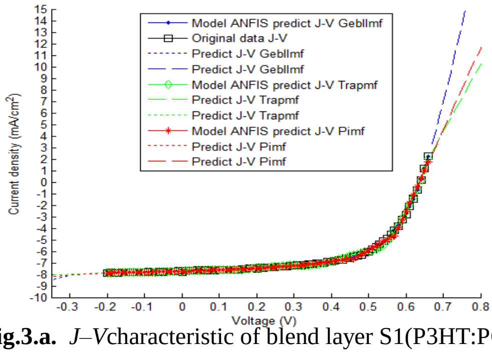

Fig.3.a. *J–V*characteristic of blend layer S1(P3HT:PC70BM)

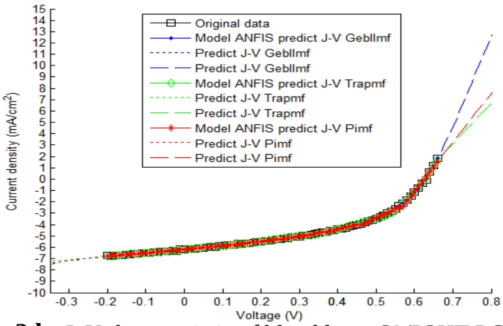

Fig.3.b. *J–V* characteristic of blend layer S2(P3HT:PC70BM).

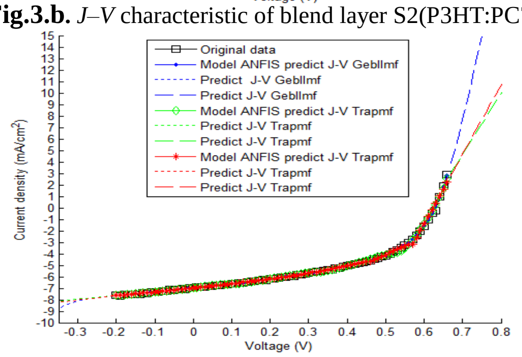

Fig. 3.c. *J–V* characteristic of blend layer S3(P3HT:PC70BM).

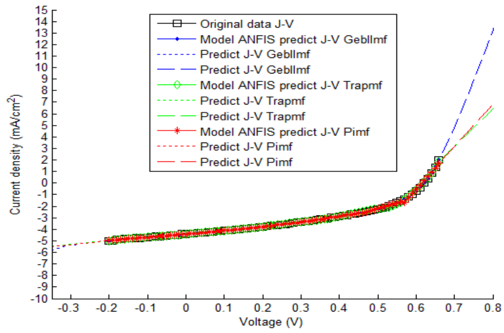

Fig. 3.d. *J–V* characteristic of blend layer S4(P3HT:PC70BM).

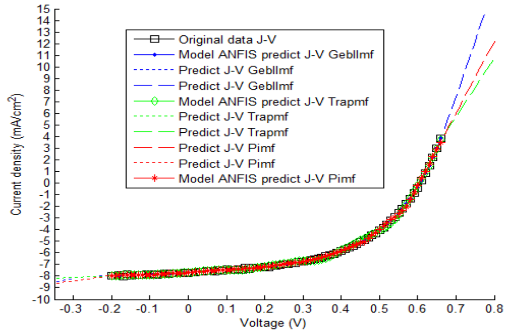

Fig.3.e. *J–V* characteristic of blend layer S5(P3HT:PC70BM).

The accuracy of prediction can evaluated by many statistical parameters such as root mean square error *RMSE*, mean absolute relative error *MARE* and determination coefficient R^2. The above parameters are given in equations (1) to (3).

$$RMSE=\sqrt{\frac{1}{n}\sum_{t=1}^{n}(A_t - F_t)^2} \quad (1)$$

$$MARE=\frac{1}{n}\sum_{t=1}^{n}\left|\frac{A_t-F_t}{A_t}\right| \times 100 \quad (2)$$

$$R^2=\frac{1-SS_E}{SS_y} \quad (3)$$

Where A_t is the actual value and F_t is the forecast value, SS_E Sum of Squares Error and SS_y Sum of Squares Total.

These parameters are calculated for different used membership functions in the ANFIS model. For seek of brevity, only the obtained results in the case S1(1:0.5) are listed in Table 1.

TABLE I. ANFIS statistical parameters for the case S1 (1:0.5)

	RMSE	MARE	*R2*
Gebllmf	0.0259	0,68	0.9998
Trapmf	0.0959	1,69	0.9979
Pimf	0.1150	2,98	0.9970

From this table, it is very clear that the ANFIS model using Gebellmf has the best quality of prediction with determination coefficient very close to the unity and little RMSE error (0,0259). In figure 4 we have also plotted the predicted values obtained with different types of membership function against the experimental results. The accuracy of prediction for each model is estimated by 1:1 line which represents 100 % accuracy.

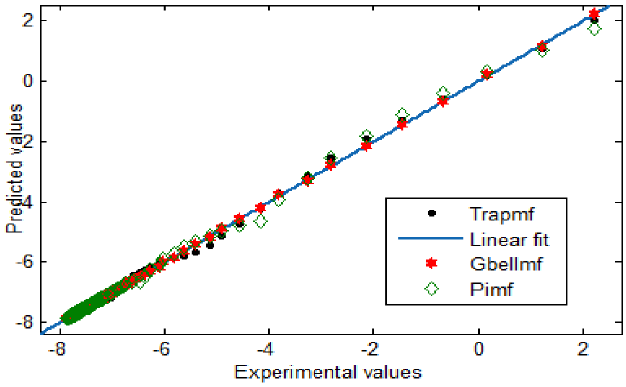

Fig.4. Linear fit of experimental and predicted values in the case of S1(1:0.5)

For all three membership functions (Gbellmf, Trapmf and Pimf), the results are very close to each other; there exists a slight difference. This observation is reinforced by the close values of R^2. The depicted statistical parameters in table 1 enhance this conclusion.

V. Conclusion

In this paper adaptive network-based fuzzy inference system ANFIS model has been used to predict the *J-V* characteristics of an organic solar cell, using three membership functions.

The used data in constructing the model are arranged in a format of two input parameters: the voltage, the mass concentration (P3HT/PCBM) and one output parameter (current density).

It has been found that the prediction accuracy using Gebllmf is better than those of Trapmf and Pimf. The performance evaluation parameters (R^2, *RMSE* and *MARE*) support this conclusion.

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