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Prediction of conductive thread consumption of transmission lines using artificial neural networks

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This paper introduces a novel approach to predict conductive thread consumption in transmission lines through the application of Artificial Neural Networks (ANNs). The study focuses on leveraging ANNs to analyse various factors influencing conductive thread usage in the production of transmission lines within textile-based electronic systems. By training the network on data collected from samples, the proposed model aims to accurately predict the conductive thread required for different transmission line configurations, enabling more efficient and cost-effective design processes in electronic textiles. In this study, transmission lines are generated using conductive thread with three different stitch types and four different stitch densities on five different fabrics, and conductive thread consumption is predicted using ANNs. The learning algorithm of the neural network is chosen as feed-forward back propagation, and the training algorithm is the Levenberg-Marquardt algorithm. Based on the obtained regression coefficient (R^2=0.98683), it is suggested that the data has a linear structure, and it is expected the structured network will have a strong estimation performance.

Keywords: Artificial neural networks, Conductive thread consumption, Stitch density, Stitch type

1 Introduction

Due to today's technological developments, advances in the field of wearable electronics have also accelerated. Cables and other hard electronic components have been replaced by soft and flexible conductive textile materials such as threads, fabrics, inks, etc. This means that the integration level of electronics into the textiles is increased. There are three levels of integration: the textile-adapted, the textile-integrated, and the textile-based integration. In the textile-adapted and textile-integrated systems, the electronic components are attached to the textile but are not fully integrated. Accordingly, they are not able to meet the fundamental requirements of textiles, such as flexibility and washability[1]. To overcome these problems, researchers have studied the integration of electronic components at the fibre or yarn level, which has resulted in textile-based integration. In this context, conventional components and wires are replaced by conductive paths and transmission lines, which are often made of textile structures directly placed at the production stage.

Textile transmission lines can be made of conductive fibres, yarns, fabrics or inks and supply power to electronic components or transmit signals. They can be implemented into a textile substrate at the production stage of fabric; electroconductive mediums can be deposited in various ways and sewed or embroidered[2-4]. Previous studies showed that lock and zigzag stitch are the main types used for smart applications[5-10]. Choudhry *et al.* developed stitch-based pressure sensors using lock stitch and investigated the influence of conductive thread and stitching parameters on sensing performance[5]. Park *et al.* fabricated a wearable strain sensor to monitor human respiration using a stretchable conductive yarn and lock stitch[6]. Tangsirinaruenart and Stylios developed a textile-based strain sensor using conductive threads and four different stitch types—304 (Zigzag stitch), 406 (2-needle multithread chain stitch: rear side), 506 (4 threads overlock stitch), and 605 (3-needles covering chain stitch) and evaluated their performance[7]. Choudhry *et al.* designed and developed textile-based piezoresistive sensors using flexible conductive threads lock stitched on fabric[8]. Aileni *et al.* studied flexible structures with electroconductive properties for wearable devices and used lock stitch[9]. Park *et al.* developed highly bendable and rotational textile structures with lock stitching conductive threads for human joint monitoring[10].

Material selection is important when producing electronic textiles, especially conductive ones like

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threads. An essential issue in thread selection, apart from its performance and appearance, is the cost of the sewing process[11]. In the case of conductive threads, it is crucial to determine the sewing thread consumption precisely due to their high cost. This way, unused stocks can be avoided, and the order quantity can be adjusted accordingly.

Existing literature has explored various methods to predict thread consumption, including geometrical models, regression models, metaheuristic optimisation models, fuzzy models, and neural networks[12-22]. The most significant parameters on thread consumption are stitch density, fabric thickness, stitch width, and elongation of the thread[11-18].

In this study, transmission lines are generated using conductive thread with three different stitch types and four different stitch densities across five fabric types, and conductive thread consumption is predicted using ANNs. By training the network on data collected from samples, the proposed model aims to accurately predict the conductive thread required for different transmission line configurations, enabling more efficient and cost-effective design processes in electronic textiles.

2 Materials and Methods

The materials used in this study consisted of one conductive and one non-conductive thread, five different non-conductive fabrics, and three types of sewing machines. The conductive thread selected was a silver-coated nylon yarn (Shieldex 235/36 dtex HC) with an average resistance value of ≤ 2.5k Ω/m. The non-conductive polyester sewing thread was a 100% sewing thread with ticket number 120. Five different non-conductive fabrics were randomly selected, and their properties are summarised in Table 1.

Three stitch types and four stitch densities were used in this study. The stitch types used were 301 lock stitch, 304 zigzag stitch, and 406 cover seaming stitch (Fig. 1). The sewing machines utilised were Garudan GF-115-107LM for lock stitch, Juki MF-7723 for cover seaming stitch, and Pfaff 332 for zigzag stitch.

In the sample production process, different stitch densities and conductive thread position combinations were used. Sewing was performed using four different stitch densities for each stitch type. The stitch densities are determined as 2.5 stitches/cm, 3 stitches/cm, 3.5 stitches/cm, and 4 stitches/cm. In addition to stitch densities, conductive threads were positioned as only needle thread, only bobbin thread and both needle and bobbin threads. In total, 180 stitch samples, each measuring 10 cm in length, were produced. Input (X) and output (Y) parameters used for the ANN structure and their minimum and maximum values are given in Table 2.

The length of the conductive threads used was measured. Sewing threads in 1 cm were cut with a razor and ripped off carefully using a seam ripper to avoid damaging the sewing thread. The length of the ripped sewing thread was measured by a measuring tape. In cases where conductive thread was used as both needle and bobbin thread, measured thread lengths were added. Similarly, if the needle thread was more than one, as is in stitch type 406, measured thread lengths were added too. Data obtained from the measurements were used to predict conductive thread consumption of transmission lines using artificial neural networks.

Artificial Neural Networks (ANNs)

ANNs are computational models that are built to simulate the networks and structures of biological nerve cells[24]. They consist of interconnected processing elements (neurons) that work together to solve specific problems[25]. They have a comprehensive acceptance in

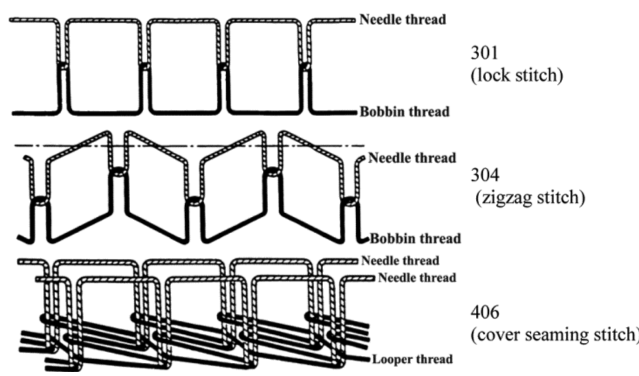

Fig. 1 — Stitch types[23]

Table 1 — Properties of non-conductive fabrics

S. No.	Fabric type	Fabric thickness, cm
1	2×2 twill woven fabric	0.33
2	2×2 twill woven fabric	0.10
3	2×2 twill woven fabric	0.15
4	Fleece fabric	0.40
5	2-thread knitted fabric	0.20

Table 2 — Input (X) and output (Y) parameters of ANN

Code	Parameter	Minimum	Maximum
X_1	Stitch type	NaN	NaN
X_2	Fabric type	NaN	NaN
X_3	Conductive thread position	NaN	NaN
X_4	Stitch densities (stitches/cm)	2.5	4
Y_1	Conductive thread consumption (cm)	1.1	13.5

NaN: Not a numeric value

many fields, such as diagnostics, identification, classification, pattern recognition, decision-making, process control, forecasting, filtering, clustering, etc., for modelling complex real-life problems[25-26].

ANNs train themselves with given input and study the process by identifying the relationships in data[27]. ANNs are composed of seven basic elements: input signals, synaptic weights, linear aggregator, activation threshold, activation potential, activation function and output signal[28-30]. In this study, an ANN was created, trained, and tested using Matlab®. The learning algorithm of our neural network is chosen as feed-forward back propagation, and the training algorithm is Levenberg-Marquardt (LM) algorithm. Levenberg-Marquardt is the most widely used optimisation algorithm. LM algorithm is particularly designed to minimise sum-of-square error functions. It performs better than simple gradient descent and other conjugate gradient methods in various problems[31-32]. It is preferred due to the speed and stability it provides in training ANNs.

The ANN architecture comprised an input layer, one hidden layer, and an output layer. The schematic diagram of the developed neural network architecture is shown in Fig. 2. Four input parameters were used: stitch type, fabric type, thread position and stitch density. The output variable was the amount of conductive thread consumption. To facilitate training, non-numerical input parameters were numerically encoded as follows: Stitch type was coded as 1 for stitch type 301, 2 for stitch type 304, and 3 for stitch type 406. Fabric type was coded as 1 for 0.33 cm thick 2x2 twill woven fabric, 2 for 0.10 cm thick 2x2 twill woven fabric, 3 for 0.15 cm thick 2x2 twill woven fabric, 4 for 0.40 cm thick fleece fabric, and 5 for 0.20 cm thick 2-thread knitted fabric. Thread position was coded as 1 for only needle thread, 2 for only bobbin thread, and 3 for both needle and bobbin thread. Stitch density was coded as 1 for 2.5 stitches/cm, 2 for 3 stitches/cm, 3 for 3.5 stitches/cm, and 4 for 4 stitches/cm.

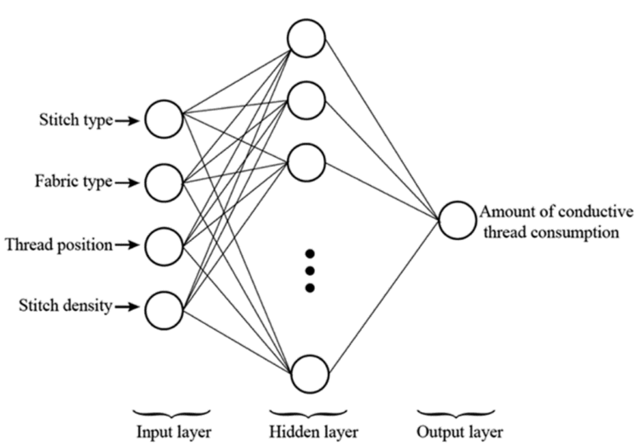

Fig. 2 — Architecture of the artificial neural network

To structure the most appropriate network, network models with different numbers of hidden layers and neurons were developed and tested, and results are detailed in Table 3. Mean Squared Error (MSE), Root Mean Squared Error (RMSE) and Mean Absolute Error (MAE) criteria were used as error performance to determine the best model. Among these values, the network with a single hidden layer containing 13 neurons delivered the best performance, achieving the lowest MSE and MAPE with the highest coefficient of determination (R^2) value. Thus, the final model was constructed using 4 inputs, 1 hidden layer with 13 neurons, and 1 output layer, as shown in Fig. 3.

If a neural network has many neurons in a particular layer, the network model becomes able to learn complex patterns in the training data. This situation causes the network to memorise training examples instead of basic patterns, used for generalisation. In conclusion, the network model provides maximum performance for training sets but fails to generalise unseen data, leading to low performance in real-world applications[33].

3 Results and Discussion

The study's main purpose is to develop a neural network that can estimate conductive thread consumption based on input parameters such as fabric type, stitch type, stitch density, and thread position. The dataset comprises 180 samples, which are randomly divided into three subsets: 70% for training, 15% for validation, and 15% for testing. In Fig. 4, it is seen that, the network model completes training at 29 epochs, achieving a minimum mean square error (MSE) of 0.25116 at 23 epochs during the network training process.

This study uses the logarithmic sigmoid function in the hidden layer and the linear activation function at the output layer. Figure 5 shows the regression plot of the network. The regression coefficient (R^2=0.99454) indicates a strong linear relationship in the data, suggesting that the developed network is capable of accurate estimation.

The test samples, which were not introduced to the network during training, were selected randomly from the dataset. A comparison of the real and estimated data is presented in Fig. 6 and Table 4.

Table 3 — Comparison of performances of tested network models

Model No.	Hidden layer number	Hidden layer neuron number	R	R^2	MSE	RMSE	MAE	MAPE
1	1	1	0,96	0,92	0,74	0,86	0,66	22,51
2	1	2	0,98	0,96	0,39	0,62	0,45	13,66
3	1	3	0,98	0,96	0,36	0,60	0,43	12,13
4	1	4	0,98	0,96	0,30	0,55	0,36	8,64
5	1	5	0,98	0,96	0,37	0,61	0,47	10,22
6	1	6	0,98	0,96	0,38	0,62	0,42	9,48
7	1	7	0,98	0,96	0,25	0,50	0,35	8,60
8	1	8	0,99	0,98	0,20	0,45	0,29	8,05
9	1	9	0,99	0,98	0,17	0,41	0,28	7,41
10	1	10	0,98	0,96	0,41	0,64	0,46	13,76
11	1	11	0,99	0,98	0,16	0,40	0,22	8,38
12	1	12	0,98	0,96	0,28	0,53	0,38	10,80
13	1	13	0,99	0,98	0,12	0,35	0,23	6,89
14	1	14	0,98	0,96	0,36	0,60	0,37	9,31
15	1	15	0,98	0,96	0,24	0,49	0,34	8,67
16	2	1-1	0,66	0,43	6,91	2,62	2,01	43,54
17	2	2-2	0,96	0,92	0,77	0,88	0,64	19,20
18	2	3-3	0,98	0,96	0,29	0,54	0,36	8,97
19	2	4-4	0,98	0,96	0,39	0,62	0,46	13,65
20	2	5-5	0,98	0,96	0,26	0,51	0,35	9,36
21	2	6-6	0,98	0,96	0,27	0,52	0,32	8,19
22	2	7-7	0,98	0,96	0,27	0,52	0,37	9,12
23	2	8-8	0,98	0,96	0,25	0,50	0,36	8,55
24	2	9-9	0,99	0,98	0,18	0,42	0,26	7,90
25	2	10-10	0,97	0,94	0,46	0,68	0,44	12,10
26	2	11-11	0,98	0,96	0,42	0,65	0,43	11,56
27	2	12-12	0,97	0,94	0,52	0,72	0,46	12,76
28	2	13-13	0,97	0,94	0,46	0,68	0,50	13,63
29	2	14-14	0,98	0,96	0,29	0,54	0,31	9,02
30	2	15-15	0,98	0,96	0,33	0,57	0,35	10,56

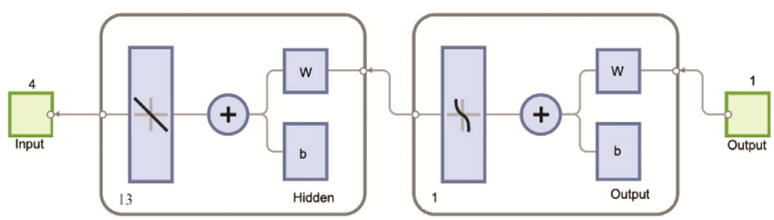

Fig. 3 — Diagram of the developed model

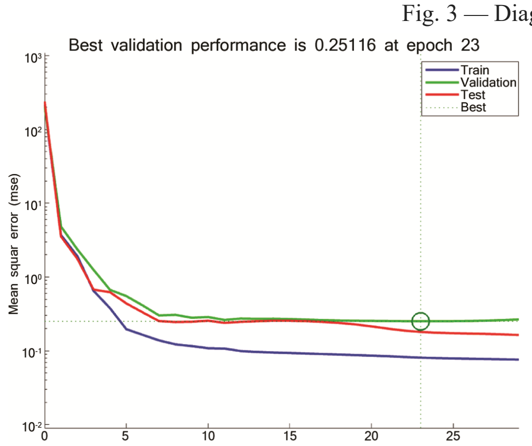

Fig. 4 — Neural network training performance

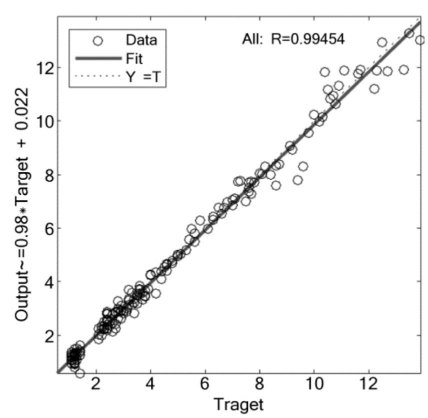

Fig. 5 — Regression plot of the network

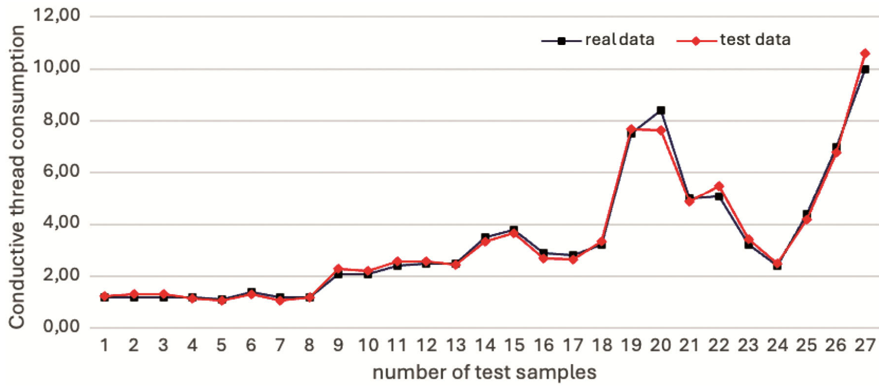

Fig. 6 — Comparison of the real data and test data

Table 4 — Comparison of the real data and test data

Stitch type	Fabric type	Thread position	Stitch density, (stitches/cm)	Conductive thread consumption (cm) (real data)	Conductive thread consumption (cm) (test data)	Absolute error %
301	1	Needle	2.5	1.20	1.24	3.33
301	1	Needle	3	1.20	1.30	8.33
301	1	Needle	3.5	1.20	1.31	9.17
301	2	Needle	3.5	1.20	1.16	3.33
301	2	Bobbin	2.5	1.10	1.08	1.82
301	4	Bobbin	3	1.40	1.30	7.14
301	5	Bobbin	3	1.20	1.07	10.83
301	1	Bobbin	4	1.20	1.19	0.83
301	2	Needle & bobbin	3	2.10	2.28	8.57
301	2	Needle & bobbin	3	2.10	2.21	5.24
301	1	Needle & bobbin	4.5	2.40	2.56	6.67
301	1	Needle & bobbin	4	2.50	2.56	2.40
301	3	Needle & bobbin	4	2.50	2.43	2.80
304	3	Needle	3.5	3.50	3.35	4.29
304	4	Needle	3.5	3.80	3.68	3.16
304	4	Needle	4	2.90	2.69	7.24
304	5	Needle	4	2.80	2.66	5.00
304	1	Bobbin	2.5	3.20	3.35	4.69
304	2	Needle & bobbin	2.5	7.50	7.69	2.53
304	4	Needle & bobbin	2.5	8.40	7.62	9.29
304	3	Needle & bobbin	4	5.00	4.90	2.00
304	5	Needle & bobbin	4	5.10	5.48	7.45
406	2	Needle	2.5	3.20	3.44	7.50
406	2	Needle	3	2.40	2.48	3.33
406	4	Needle	4	4.40	4.21	4.32
406	3	Bobbin	4	7.00	6.78	3.14
406	2	Needle & bobbin	3.5	10.00	10.6	6.00
					Mean error %:	5.20

As an example of a comparison process, concerning a stitch with stitch type 304 and 4 stitches/cm on a fleece fabric and both needle and bobbin thread are conductive thread, conductive thread consumption is estimated as 4.90 cm by the network model. The measured real value in the experiments is 5 cm. According to these results, the absolute error is determined as 2%, which means the structured network model could estimate the relevant consumption value with 98%.

4 Conclusion

This study employs a Feed-forward back propagation ANN model and sigmoid transfer function in the hidden layer and a linear function in the output layer to estimate the conductive thread consumption under varying input parameters. The model, trained on 180 samples, demonstrates high accuracy, with a regression coefficient (R^2) of 0.99454 and a mean absolute error of 5.20%. These results confirm that the structured network is effective in predicting conductive thread consumption for different fabric and stitching scenarios. The ANN model is shown to contribute significantly to the optimisation of textile electronics, enabling improvements in material efficiency, cost reduction, and process precision. Its implementation can support smarter decision-making in the design and manufacturing stages of electronic textile systems, where accurate material estimates are essential.

Availability of Data and Materials

The data supporting this study's findings are available on request from the corresponding author.

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