Spiking Neural Network in Precision Agriculture

Nadia Adnan Shiltagh
Assistant professor Dr.
Computer Engineering/ Baghdad University
E-mail:dr-nadiaat@hotmail.com

Hasnaa Ahmed Abas
Computer Engineering/Baghdad University
E-mail:en_hasnaa@yahoo.co.uk

ABSTRACT

In this paper, precision agriculture system is introduced based on Wireless Sensor Network (WSN). Soil moisture considered one of environment factors that effect on crop. The period of irrigation must be monitored. Neural network capable of learning the behavior of the agricultural soil in absence of mathematical model. This paper introduced modified type of neural network that is known as Spiking Neural Network (SNN). In this work, the precision agriculture system is modeled, contains two SNNs which have been identified off-line based on logged data, one of these SNNs represents the monitor that located at sink where the period of irrigation is calculated and the other represents the soil. In addition, to reduce power consumption of sensor nodes Modified Chain-Cluster based Mixed (MCCM) routing algorithm is used. According to MCCM, the sensors will send their packets that are less than threshold moisture level to the sink. The SNN with Modified Spike-Prop (MSP) training algorithm is capable of identifying soil, irrigation periods and monitoring the soil moisture level, this means that SNN has the ability to be an identifier and monitor. By applying this system the particular agriculture area reaches to the desired moisture level.

Key words: precision agriculture, wireless sensor network, spiking neural network, modified chain-cluster based mixed.

الشبكة العصبية المتصاعدة في الزراعة الدقيقة

أ.م.د. نادية عدنان شلتاغ
هندسة الحاسبات/جامعة بغداد

حسناء احمد عباس
هندسة الحاسبات/جامعة بغداد

الخلاصة

في هذا البحث, تم عرض نظام الزراعة الدقيقة بالاعتماد على شبكة الاستشعار اللاسلكية. تعتبر رطوبة التربة واحدة من العوامل البيئية المؤثرة على المحصول. فترة السقي يجب ان تراقب. الشبكات العصبية لها القدرة على تعلم سلوك التربة الزراعية بغياب التمثيل الرياضي. هذا البحث يقدم نوع معدل من الشبكة العصبية التي تسمى بالشبكة العصبية المتصاعدة. في هذا العمل, النظام الزراعي الدقيق, الذي تم تمثيله, يحوي اثنين من الشبكات العصبية المتصاعدة SNN التي تم تعريفها بدون اتصال (off-line) بالاعتماد على بيانات مسجلة, واحدة من هاتين SNN تمثل المُراقب الذي يقع في الوحدة المركزية حيث يحسب فترة السقي و الاخر يمثل التربة, بالاضافة الى ذلك , لتقليل الطاقة المستهلكة لعقد الاستشعار, تم استخدام خوارزمية توجيه معدلة (MCCM). وفقا لهذه

الخوارزمية (MCCM) فأن عقد الاستشعار سترسل بياناتها الاقل من عتبة مستوى الرطوبة الى الوحدة المركزية . الشبكة العصبية المتصاعدة مع خوارزمية التدريب المعدلة MSP قادرة على : تعريف التربة, تعريف فترة السقي و مراقبة مستوى رطوبة التربة, وهذا يعني ان SNN يمكنها ان تكون مُعرف و مُراقب. بتطبيق هذا النظام فأن المنطقة الزراعية ستصل الى مستوى الرطوبة المطلوبة.

1. INTRODUCTION

In Precision Agriculture (PA), various parameters including soil type and temperature vary dramatically from one region to the other and therefore any irrigation system must be flexible enough to adapt to the constraints**, Kumar**, **et al., 2013.** Wireless Sensor Networks (WSNs) can play an important role because of their ability of providing real-time data collected by spatially distributed sensors. More specifically, a WSN is a wireless network composed by a set of autonomous, low-power, and low-cost devices (called *nodes*) using sensors to cooperatively monitor physical quantities. WSNs have been already used for PA purposes especially for monitoring environmental parameters**, Martinelli, et al., 2009.** PA is a new development in traditional agriculture. In PA, production environment is monitored, and the monitored data is used to derive the most suitable environment management decision which employs control and adjustment solutions to obtain better product yield. Greenhouse shed is one of the typical means in PA. In order to achieve precision control to the production environment, it is necessary to perform three tasks: Firstly, monitoring parameters such as temperature, Secondly, control and management decision is determined based on the analysis of the collected data. Finally, based on the control decision, automatic or manual control mechanism is implemented, Xia**, et al., 2011.** PA ensures quicker response time to adverse climatic conditions, better quality control of the produce and yet a lower labor cost **,Anurag et al., 2008.** WSN is a major technology that drives the development of PA. An important issue that arises in PA is the type of parameters to be sensed, which apart from the regular environmental parameters like temperature, humidity**, Valada, et al., 2012.**

2. PRECISION AGRICULTURAL SYSTEM AND SPIKING NEURAL NETWORK

General block diagram of agricultural soil for precision agricultural system is shown in **Fig. 1.** To construct a precision agricultural system, this requires two SNN. These two SNNs must be identified and trained through Modified Spike-Prop training algorithm (MSP).

2.1 Spiking Neural Network Structure

The structure of SNN is shown in **Fig. 2**. The feedforward SNN is constructed in three layers: two units in input layer H, seven units in hidden layer I and one unit in output layer J. Each connection between input and hidden layer, hidden and output layer consists of six delayed sub-connection or synapses k as shown in **Fig. 3**. Number of hidden units and number of synapses in each sub-connection are chosen through trial and error.

2.2 The Modified Spiking Neural Network Training Algorithm

In MSP the starting of processing information is begun after encoding process. In encoding process, the real information RI is encoded with respect to time interval T such that the smallest value in the pattern R_{min} takes the largest value of time interval t_{max} and the largest value in the pattern R_{max} takes the smallest value of time interval t_{min}, the actual coded information $t_h^{(act)}$ will be calculated by Eq. (1) **,Oniz, et al, 2008.**

$$t_h^{(act)} = t_{max} - round(\, t_{min} + \frac{(RI-R_{min})(t_{max}-t_{min})}{(R_{max}-R_{min})}) \quad (1)$$

Where $round$ is a function that approximates the float element to the nearest integer.

The decoding equation can be derived from Eq. (1) by solving for RI.

$$RI(t_j) = \frac{\left(t_{max}- t_j-t_{min}\right)\times(R_{max}-R_{min})}{(t_{max}-t_{min})} + R_{min} \quad (2)$$

MSP algorithm passes into two phases. In the first phase, feedforward phase, each neuron can spike at most once only during the time interval T, when its membrane potential m exceeds threshold value ϑ. The feedforward phase usually begins from hidden layer I and check every neuron i consequently if it is spiked or not. If the neuron i is spiked the algorithm goes to the next neuron $i+1$ in the same layer, else MSP algorithm calculates the membrane potential $m_i(t)$ according to Eq. (3) based on input spikes $t_h^{(act)}$of neuron h at input layer H.

$$m_i(t) = \sum_{h=1}^{NH} \sum_{k=1}^{D} w_{hi}^k(R)\, \varepsilon(t - t_h^{(act)} - d^k) \quad (3)$$

Where w_{hi}^k : connection weight between neuron h and neuron i for the synapse k.
d^k : delay value of the synapse k.

$$\varepsilon(t) = \frac{t}{\tau}\, e^{1-\frac{t}{\tau}} \quad (4)$$

Where τ is the time-constant and $\varepsilon(t) = 0$ for $t \le 0$ to insure causality **,Thiruvarudchelvan,et al, 2013.**

If $m_i(t)$ exceeds threshold at particular instant t , then the neuron i will be forbidden from spiking more during the remaining time interval T, else it will be reset in next instant $t+1$. After second layer's neurons has finished, the algorithm goes to the output layer J and repeat the same procedure, but in this case the spikes of hidden layer will be inputs to the output neurons. When T interval has been finished, then the backpropagation phase begins. After feedforward phase has been finished the second phase begins where the synapses' weights of connection will be updated. Opposed to feedforward the backpropagation begins from output layer and return back to the hidden layer.

The two phases will be repeated, if the Root Mean Square Error (RMSE) is less than desired value of error. The learning rate η will be updated after end of each epoch according to the Eq. (5) **,Huijuan, et al. 2012.**

$$\eta(epoch+1) = \begin{cases} a\,.\eta(epoch) \text{ if } error(epoch+1) < error(epoch) \\ b.\eta(epoch) \quad \text{if } error(epoch+1) > c.error(epoch) \\ \eta(epoch) \quad \text{if } error(epoch+1) = error(epoch) \end{cases} \qquad (5)$$

Where a, b and c are constants and their values are chosen by trial and error.

3. SYSTEM IDENTIFICATION

The input to the soil, which represents agricultural soil, is the Irrigation Period (IP) and the output is Moisture Level (ML).The mathematical model of the soil that will be identified depending on logged data. Soil can be considered as input/output system with unknown structure and unknown parameters, in the training process mapping between input-output data will be done by SNN through MSP training algorithm. The Non-Parametric identification is done.

Fig. 4 shows the identification of soil using SNN. The present state of IP and Actual Moisture Level (AML) are fed as the inputs to spiking neural network. Moisture Level Spiking Neural Network (MLSNN) is trained off-line to adapt MLSNN's weights to optimize soil response. Weights are updated according to the error between the output of soil (ML) and the output of MLSNN ($\widehat{ML}$), as described in Eq. (6).

$$error = ML - \widehat{ML} \qquad (6)$$

The input signal of soil, which is IP, must be calculated and processed. Another plant, which is called irrigation plant, is used to calculate IP. Irrigation plant is identified based on logged data. Logged data is forwarded to Irrigation Period Spiking Neural Network (IPSNN) which is trained off-line by MSP training algorithm. The inputs to IPSNN are AML and Desired Moisture Level (DML) and the output is estimated Irrigation Period ($\widehat{IP}$). **Fig. 5** Shows block diagram of the irrigation plant identification.

4. SPIKING NEURAL NETWORK WITH MODIFIED SPIKE-PROP ALGORITHM AGRICULTURAL SYSTEM

The objective is to construct an agricultural model to keep the moisture level around the desired set-point after applying particular irrigation period to avoid dry or too much wetted soil. **Fig. 6** shows the block diagram of the agricultural system. The monitor at first, encode the real values of moisture level with respect to time. Then the following procedure will be repeated for all encoded data:

1. Monitoring plant or IPSNN produces IP according to the inputs: AML and DML.
2. IP will be set to MLSNN. MLSNN will produce $\widehat{ML}$ according to IP and AML. The current $\widehat{ML}$ must be around DML value.

When all packets have been completed, the sink will return the IPs values to the sensors. As a result all the coverage areas have their moisture level monitored by sink thereby saving the moisture level around desired moisture level.

5. SIMULATION RESULTS

The simulation of precision agriculture system model is explained by using Spiking Neural Network (SNN) with Modified Spike-Prop training algorithm (MSP). The agricultural system is simulated using MATLAB R2012a simulator. The simulation of wireless sensor network for precision agriculture system is shown in **Fig. 7**. The network consist of one hundred stationary sensor nodes placed in a $(25 \times 100)\ meter$ with one sink node. Network specification mentioned in **Table 1**.

The compression between Modified Chain-Cluster based Mixed (MCCM) and Chain-Cluster based Mixed (CCM) routing algorithm with respect to energy consumption of cluster head nodes is shown in the **Fig. 8**. Minimum and maximum values of energy consumption for both CCM and MCCM are: (0.0037, 0.0568) and (0.0030, 0.0511) respectively, so the enhancement percentage of energy consumption is from 10% to 18.9%.

5.1 Identification Results

The general specification of SNN with MSP training algorithm is presented in the **Table 2**. The spike-response functions ε with $\tau = 3$ for one connection of six synapses are shown in **Fig. 9**. Notice that first curve starts from 1 because ε function has one delay, also the final curve starts with 6 because ε function has six delays. Summation of spike-response functions of **Fig. 9** along T is shown in **Fig. 10**. The identification process is done for moisture level and irrigation plant using SNNs:

5.1.1 Irrigation period spiking neural network identification

Irrigation Period Spiking Neural Network (IPSNN) specification is mentioned in Table (2). IPSNN of **Fig. 5** is identified through MSP training algorithm by using logged training samples. The training samples are: Actual Moisture Level (AML), Desired Moisture Level (DML) and Irrigation Period (IP) values as shown in Table (3). The training samples of Table (3) are converted to spikes, then they enter to the training stage. After the IPSNN is trained for 100 epochs, output of IPSNN ($\widehat{IP}$) will converge to the desired IP and the final values of the weights are saved. Result of IPSNN identification is shown in **Fig. 11**. To check validation of identified IPSNN, the saved weights of identification stage are used with another set of data; the result of validation is shown in **Fig 12**.

5.1.2 Moisture level spiking neural network identification

Moisture Level Spiking Neural Network (MLSNN) specification mentioned in **Table 2**. MLSNN of **Fig. 4** is identified based on logged data. **Fig. 13** shows MLSNN identification. As it is clear from **Fig. 13**, the output of MLSNN ($\widehat{ML}$) is converged to the Desired Moisture Level (DML) this means that MLSNN provide acceptable moisture level for corresponding part of agricultural area. MLSNN is trained for 100 epochs and the final weights will be saved. After training has finished, the RMSE reaches 0.500. To check validation of identified MLSNN, the saved weights of identification stage are used as initial weights with another set of data; the result of validation is shown in **Fig. 14**.

5.2 Simulation Results of Agricultural System

Sensor nodes packets are random values between 3% and 13% of moisture level; they will be transmitted to the sink node using MCCM. The moisture level of the first strip reaches to the DML as shown in **Fig. 15**. **Table 4** presents the AML, DML, and IP for the first strip after decoding. As it is clear from Table (4), IP values are proportional to the difference between AML and DML. For example at the first sensor node the difference between AML and DML is 26.86 so the IP is 11.98, but at second sensor node the difference between AML and DML is 10.07 so the IP is 5.90 and it is less than first IP and not vice versa. When the AML is greater than DML this means that the corresponding agricultural area does not need irrigation; therefore; the IP will be zero like node 26 its moisture is 10.89 and the DML is 10 so IP is zero. IP values for all nodes are shown in **Fig. 16.**

Moisture level of all sensor nodes in the network is shown in **Fig. 17**, these values are coded values and the real values are obtained after decode them. **Fig. 18** shows the real values of **Fig. 17**. As it is clear the output of MLSNN, converges to the DML, then all agricultural area is at desired moisture level.

6. CONCLUSIONS

From the simulation results, the following points can be noted:

- MCCM is better than CCM, because in MCCM the sensor node transmit its packet if the moisture level is less than the threshold value; this means that the energy consumption is less. The energy consumption is diminished in proportional with number of transmitted packets. From other side of view, MCCM reduce the congestion and overhead on the network.
- SNN with modified Spike-Prop training algorithm learned quickly, it has good results in identification of the moisture level and the irrigation.
- SNN has capability of monitoring IP of **Fig. 6**, and this is proved in the results as shown in **Figs. 16** and **17**.

REFRENCES

- Anurag, D., Roy, S., and Bandyopadhyay, S., May 2008, *Agro-Sense: Precision Agriculture Using Sensor-Based Wireless Mesh Networks*, First ITU-T kaleidoscope academic conference – innovation in NGN: future Network and service, IEEE.

- Capraro, F., Patifio, D., Tosetti, S., and Schugurensky, C., April 2008, *Neural Network-Based Irrigation Control for Precision Agriculture*, International Conference on Networking, Sensing and Control, IEEE.

- Huijuan, F., Jiliang, L., and Fei, W., July 2012, *Fast Learning in Spiking Neural Networks by Learning Rate Adaptation*, Chinese Journal of Chemical Engineering.

- Kumar, N., D., Pramod, S., and Sravani, C., August 2013, *Intelligent Irrigation System*, International Journal of Agricultural Science and Research, ISSN 2250-0057, Vol. 3, Issue: 3.

- Martinelli, M.,Ioriatti, L.,Viani, F., Benedetti, M. and Massa, A., July 2009, *A WSN-Based Solution for Precision Farm Purposes*, IEEE.

- Oniz, Y., Kaynak, O., and Abiyev, R., March 2013, *Spiking Neural Networks for the Control of a Servo System*, IEEE.

- Thiruvarudchelvan, V., Crane, J., W., and Bossomaier, T., April 2013, *Analysis of SpikeProp Convergence with Alternative Spike Response Functions*, IEEE.

- Valada, A., Kohanbash, D., and Kantor, G., 2012, *Design and Development of a Wireless Sensor Network System for Precision Agriculture*, citeseer.

- Xia, J., Tang, Z., Shi, X., Fan, L., and Li, H., December 2011, *An environment monitoring system for precision agriculture based on wireless sensor networks*, Seventh International Conference on Mobile Ad-hoc and Sensor Networks.

Symbols

Symbol	Description	Unit
$\boldsymbol{d^k}$	Delay of specific synapse	msec
$\boldsymbol{m_i(t)}$	Membrane potential of hidden layer neurons	Unit less
$\boldsymbol{t_h^{(act)}}$	Actual spiking time of neurons at input layer	msec
$\boldsymbol{w_{hi}^k}$	Weight between input and hidden layer	Unit less
$\boldsymbol{NH}$	Number of neuron in input layer	Unit less
$\boldsymbol{RI}$	Real input pattern	Unit less
$\boldsymbol{T}$	Time interval	msec
$\boldsymbol{h}$	Neuron sequence in input layer	Unit less
$\boldsymbol{i}$	Neuron sequence in hidden layer	Unit less
$\boldsymbol{t}$	Current time	msec
$\boldsymbol{\varepsilon}$	Spike response function	msec
$\boldsymbol{\eta}$	Learning rate	Unit less
$\boldsymbol{\vartheta}$	Threshold value for spiking	Unit less

Table 1. Wireless sensor network specification.

Parameter	**Value**
Number of nodes	$100\ node$
Number of strips	$5\ strip$
Number of nodes in one strip	$20\ node$
Sink node position	(120,13)
Coverage area	$100 \times 25\ meter$
Distance between two nodes vertically	$5\ meter$
Distance between two nodes horizontally	$5\ meter$
Packet size	$2\ k\ bit$
routing	MCCM algorithm
Energy of running transmitter	$50\ nJ/bit$
Energy of running amplifier	$100\ pJ/bit * meter^2$

Table 2. SNN specification.

Parameter	**Value**	**Unit**	**Description**
network topology	2,7,1	Unit less	Number of units in Input/Hidden/output
$\boldsymbol{\eta}$	0.00l	Unit less	Learning rate value initially
$\boldsymbol{a, b, c}$	1.38 , 1.14 , 0.8	Unit less	Constants of adaptive learning rate
$\boldsymbol{\tau}$	3	msec	Time constant
$\boldsymbol{\vartheta}$	1.5	Unit less	Threshold value for spiking
$\boldsymbol{T}$	1-80	msec	Time interval
$\boldsymbol{D}$	6	msec	Number of delay synapses per connection
$\Delta \boldsymbol{t}$	0.1	msec	Step size
$\boldsymbol{w}$	[0-1]	Unit less	Initial weights of hidden and output layer

Table 3. Training samples values of identification, **Capraro, et al., 2008.**

No.	AML(%)	IP(hr.)	DML(%)
1	5	9.5	32
2	17	7.3	27
3	7	15	45
4	20	10.3	35
5	8	3.8	15
6	7	1.1	8
7	3	9.3	32
8	11	8.6	29
9	10	13	42
10	20	9.7	32
11	11	8	28
12	10	14	45
13	23	9.4	32
14	12	9.8	34
15	13	14	45
16	12	5.7	20
17	8	8.3	28
18	10	3.5	15
19	4	8.5	29
20	18	8	28

Table 4. AML, DML and IP for the first strip.

NO.	AML (%)	IP(hr.)	DML (%)
1	11.14	11.98	38
2	8.93	5.90	19
3	4.39	12.55	40
4	3.84	5.90	19
5	3.49	3.24	10
6	9.01	3.26	10
7	9.53	10.27	33
8	5.98	6.84	22
9	3.98	10.08	32
10	8.24	4.38	14
11	3.34	2.86	9
12	6.43	14.06	45
13	8.82	11.03	35
14	5.78	8.75	28
15	9.97	12.55	40
16	4.75	6.85	22
17	12.44	4.76	15
18	9.07	4.38	14
19	10.72	3.83	12
20	5.13	11.98	38

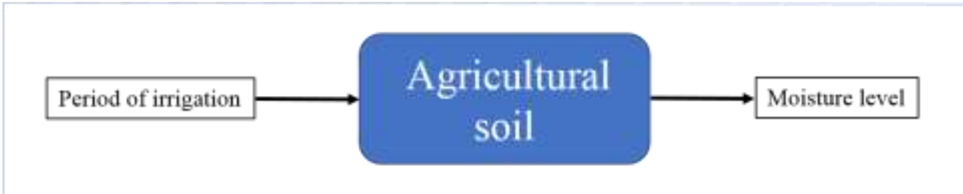

Figure1. General system block diagram.

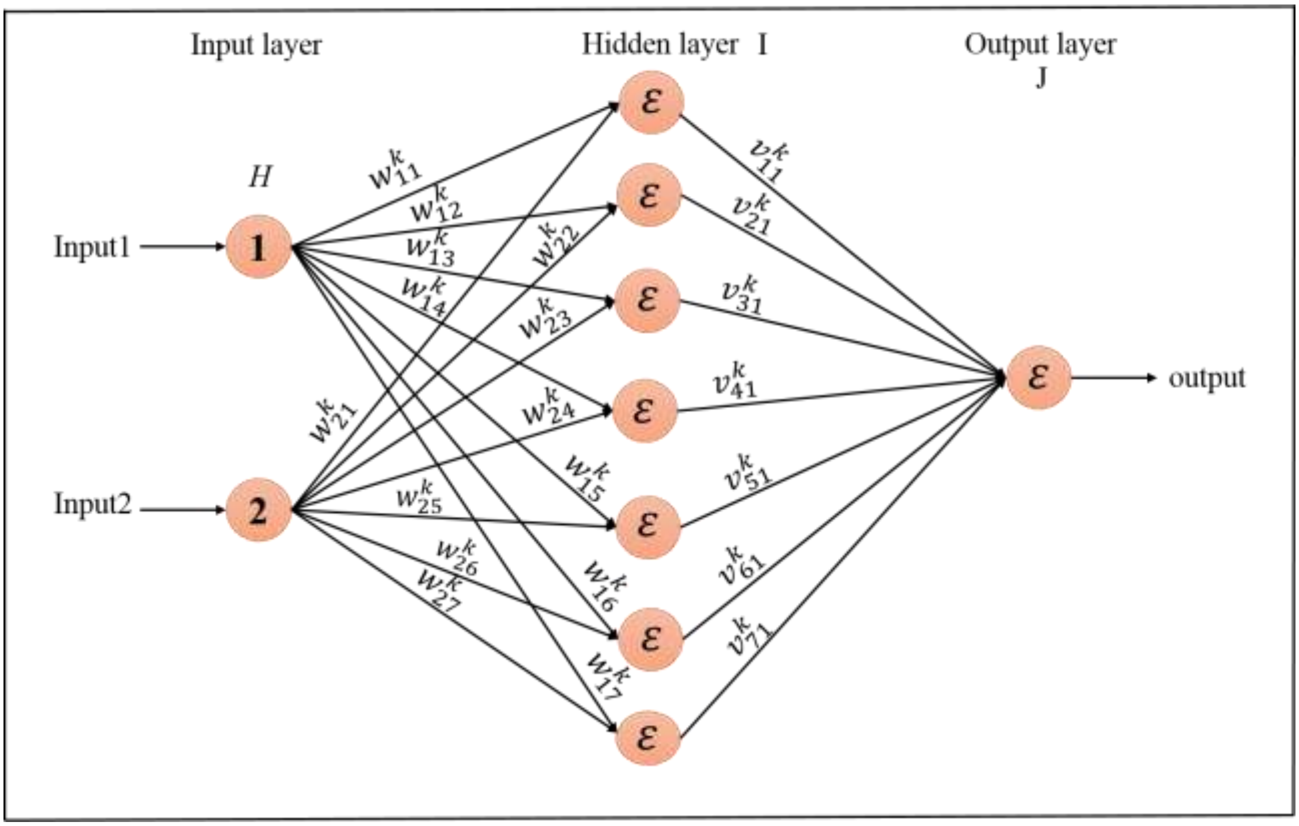

Figure 2. Structure of SNN.

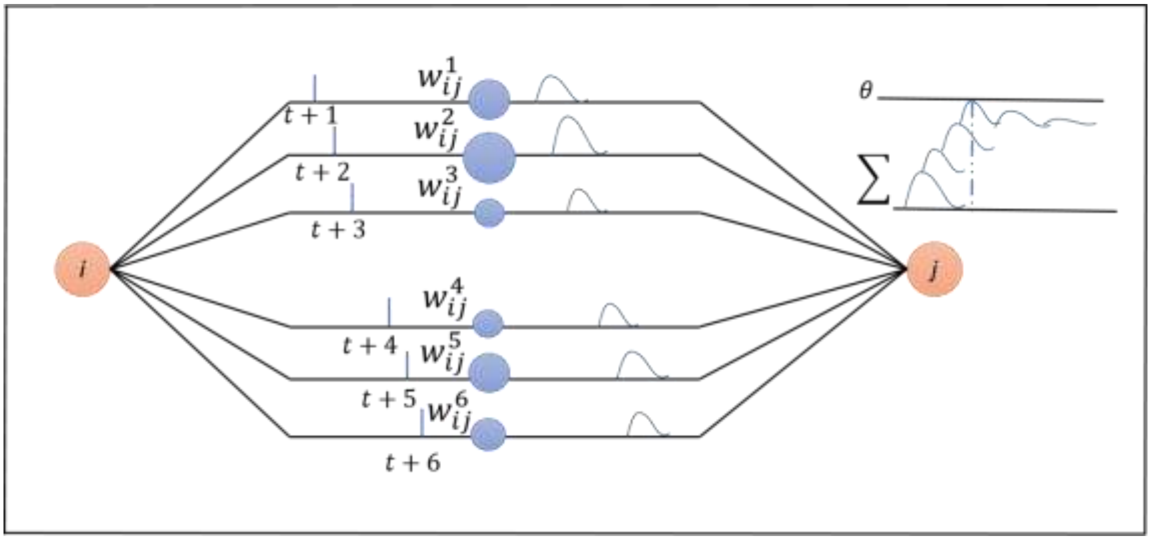

Figure 3. Sub-connection consist of six synapses.

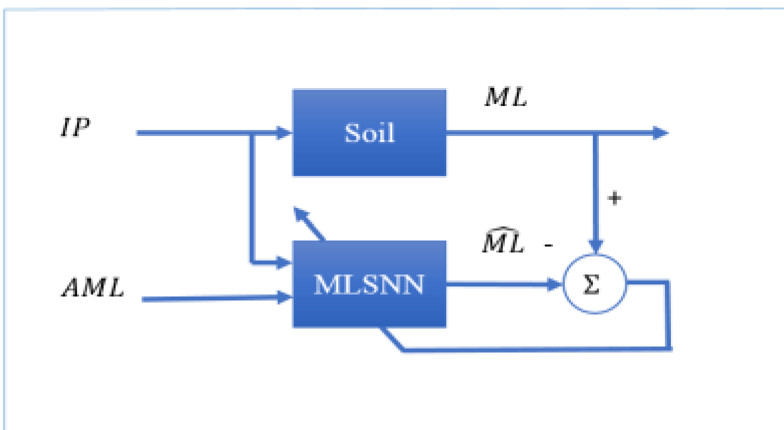

Figure 4. Soil plant identification.

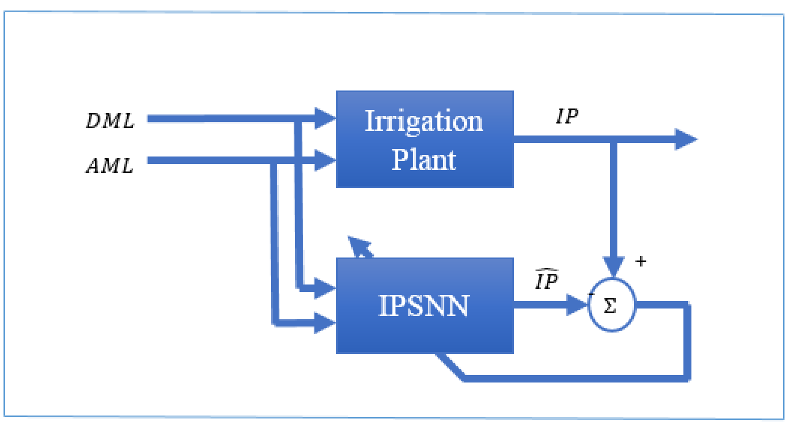

Figure 5. Identification of Irrigation Length Interval.

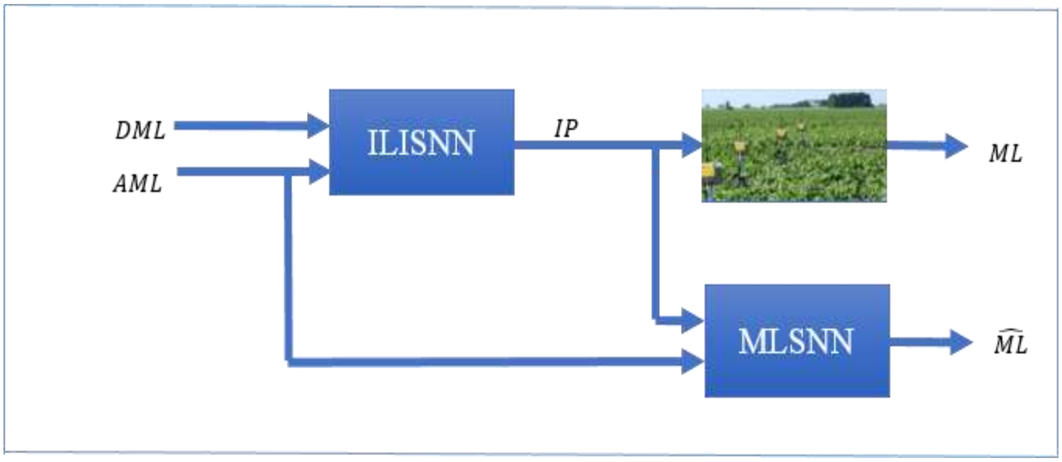

Figure 6. Block diagram of agricultural system.

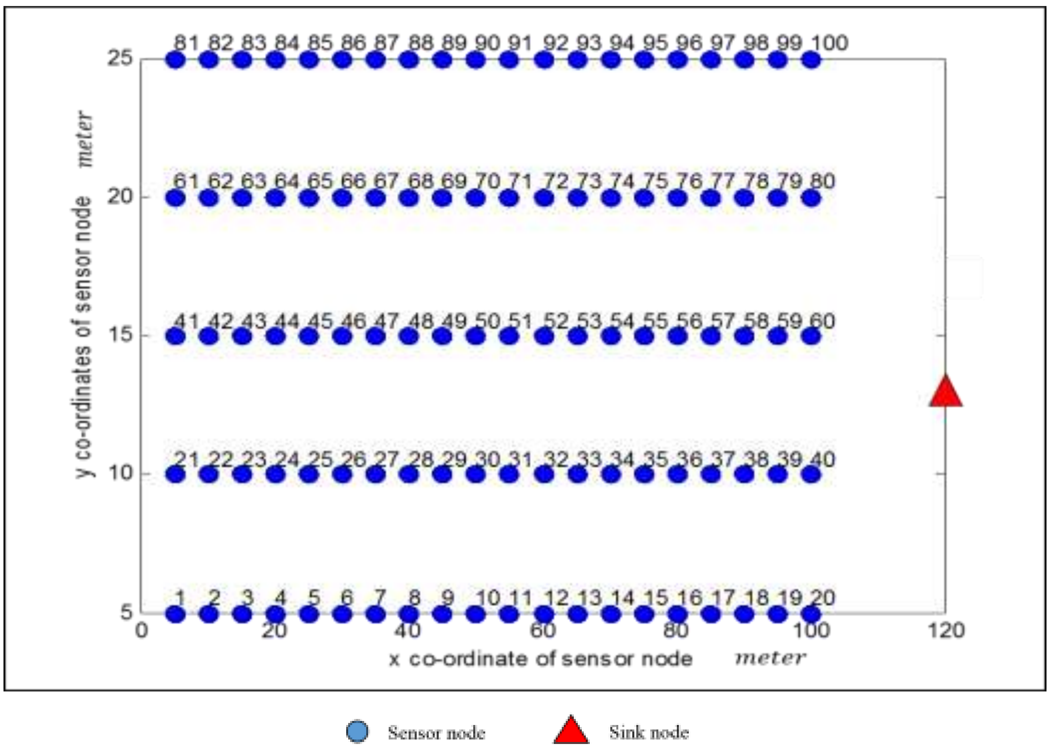

Figure 7. Sensor nodes distribution in particular area.

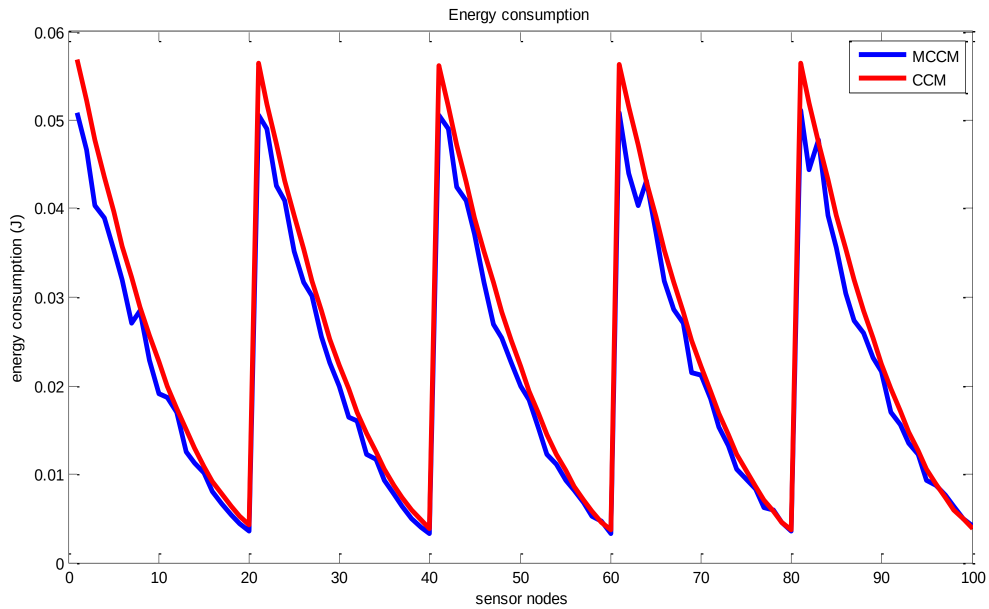

Figure 8. The compression of energy consumption.

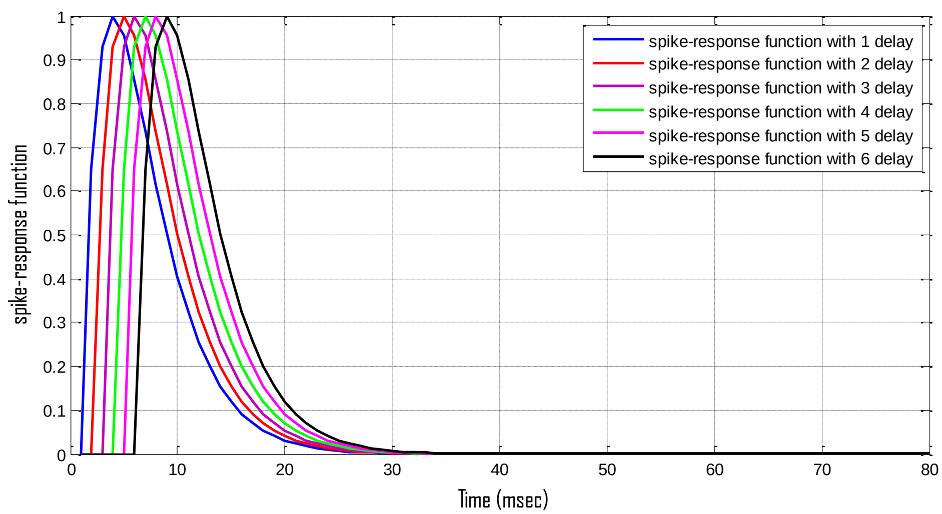

Figure 9. Spike-response functions for one connection.

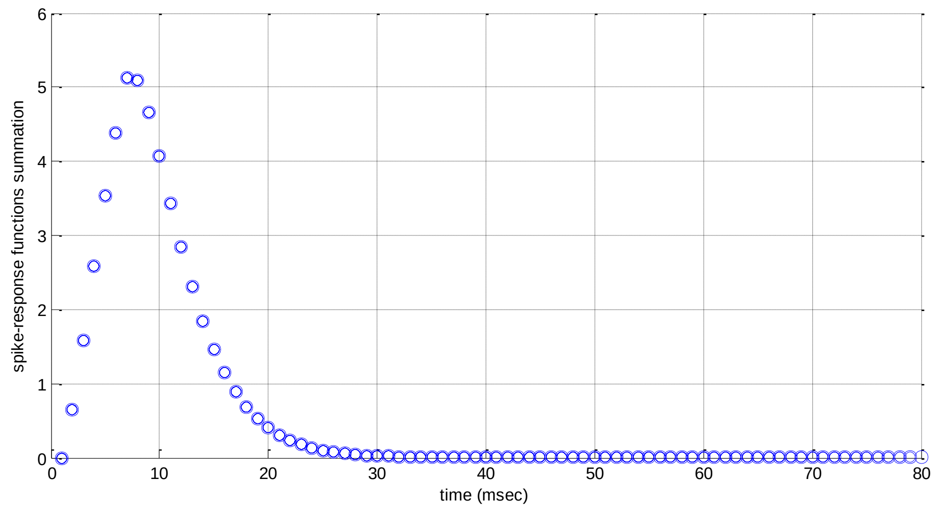

Figure10. Summation of spike-response function.

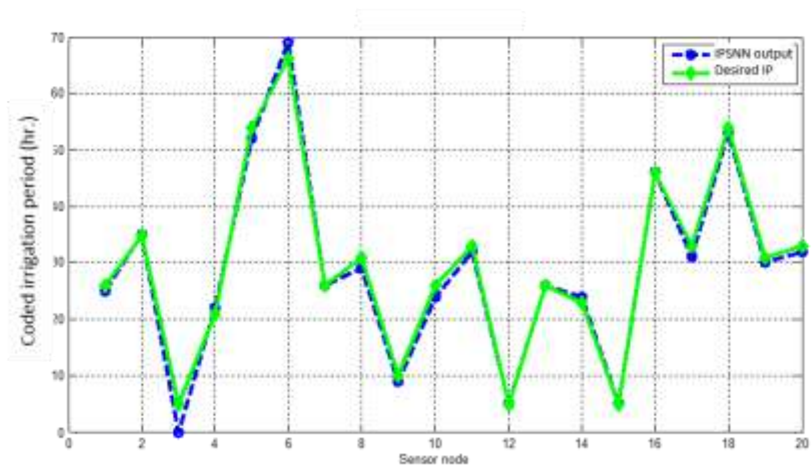

Figure 11. IPSNN identification.

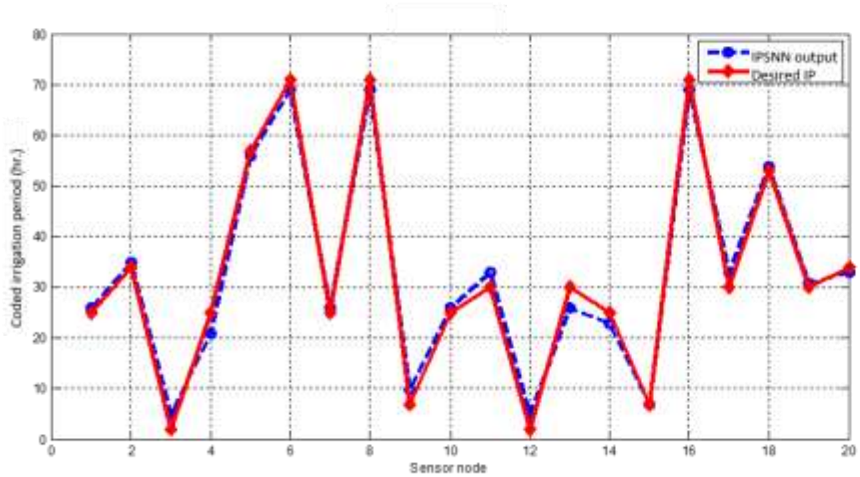

Figure 12. IPSNN validation.

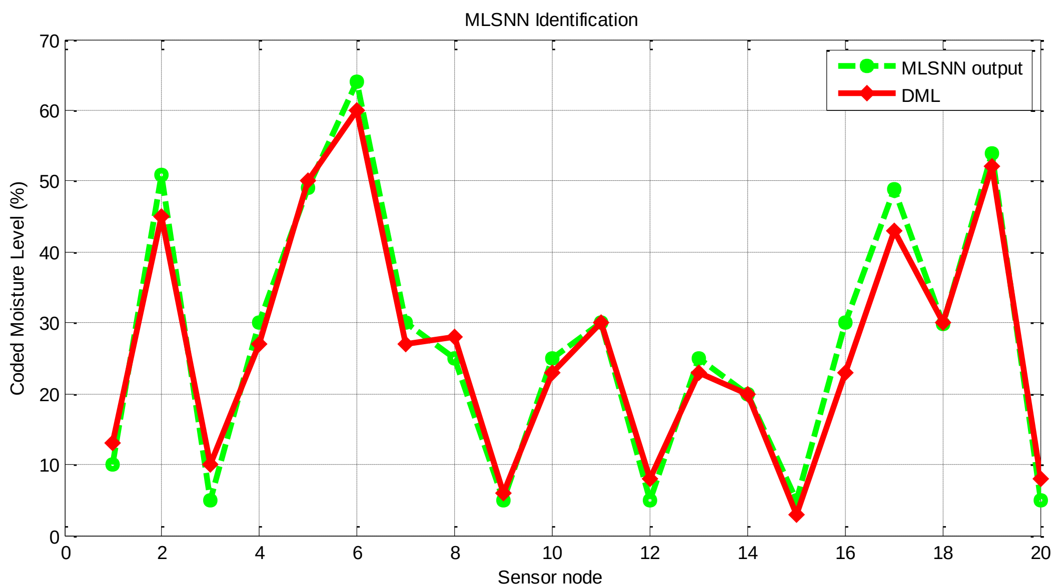

Figure 13. MLSNN identification.

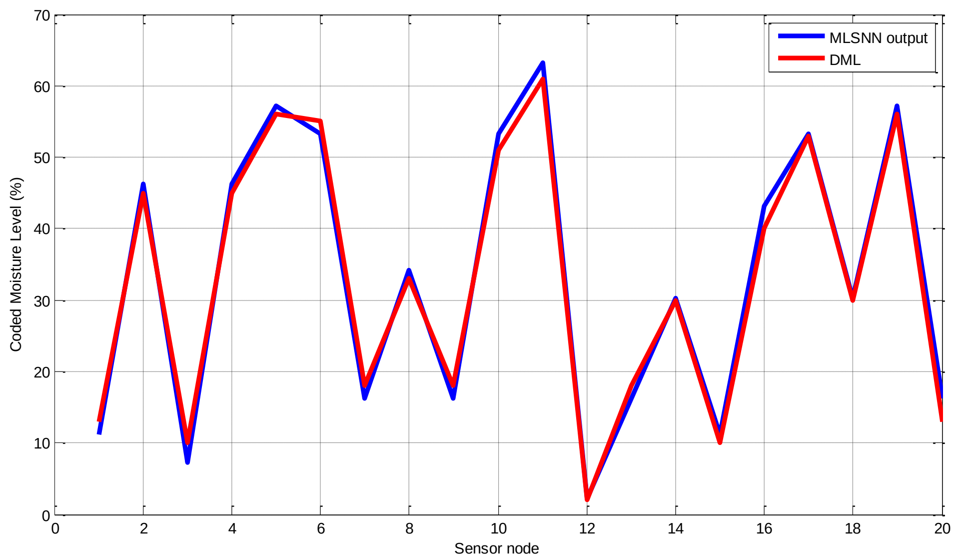

Figure 14. MLSNN validation.

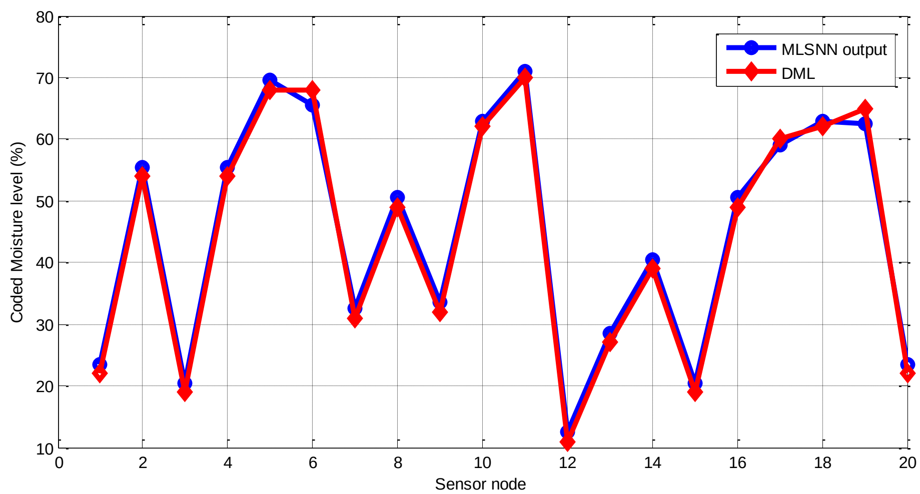

Figure 15. Moisture level of the first strip.

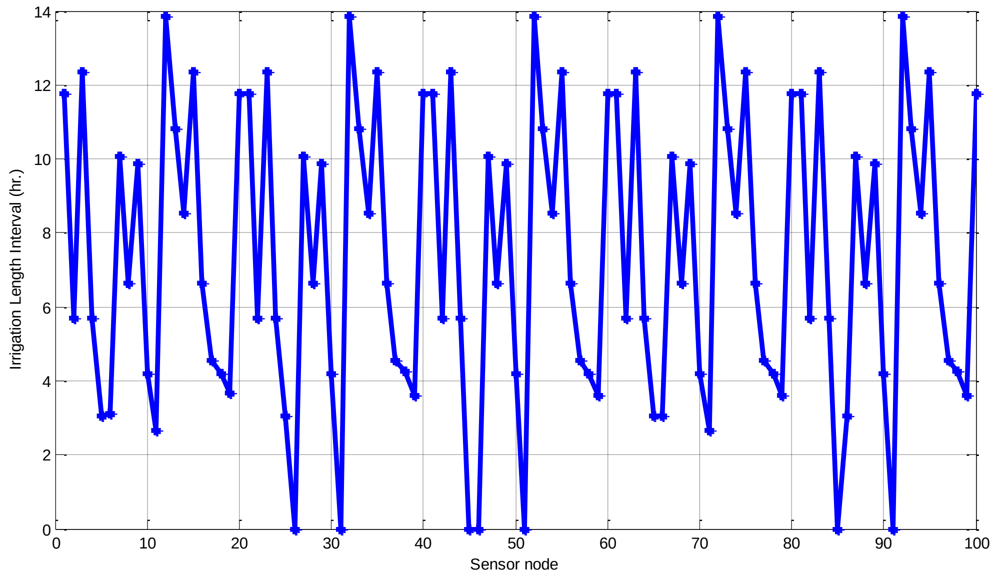

Figure 16. Irrigation length interval required for all nodes.

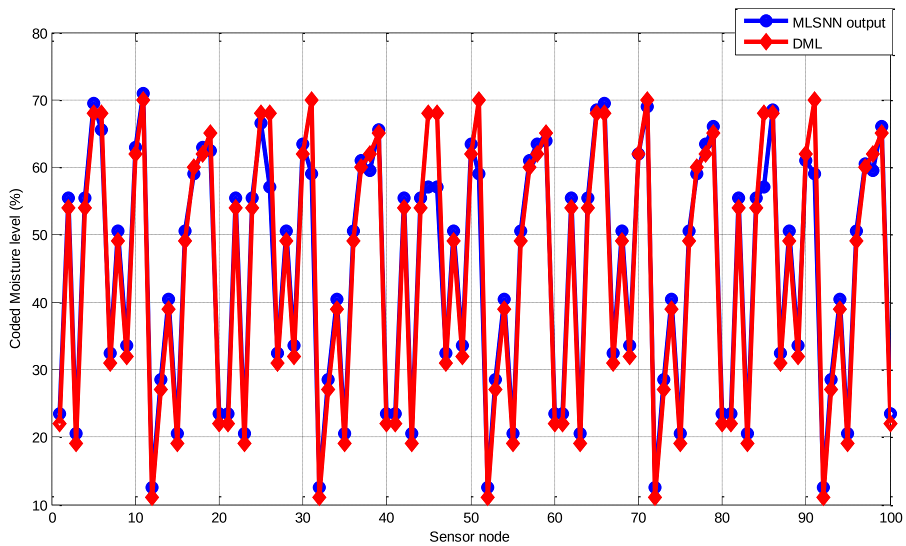

Figure 17. The moisture level for all nodes.

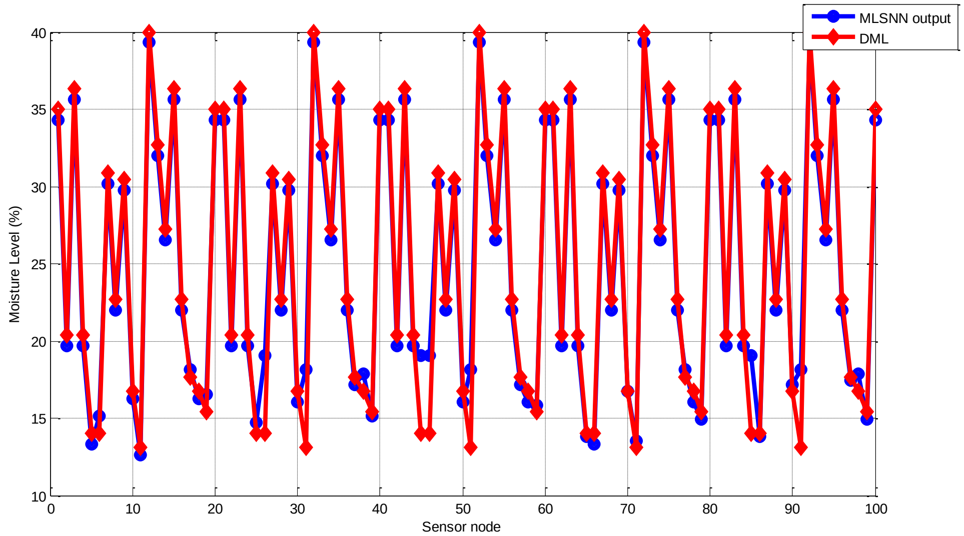

Figure 18. Moisture level for 100-node after decoding.