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Artificial Neural Synchronization Using Nature Inspired Whale Optimization

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ABSTRACT In this article, a whale optimization-based neural synchronization has been proposed for the development of the key exchange protocol. At the time of exchange of sensitive information, intruders can effortlessly perform sniffing, spoofing, phishing, or Man-In-The-Middle (MITM) attack to tamper the vital information. Information needs to be secretly transmitted with high level of encryption by preserving the authentication, confidentiality, and integrity factors. Such stated requirements urge the researchers to develop a neural network-based fast and robust security protocol. A special neural network structure called Double Layer Tree Parity Machine (DLTPM) is proposed for neural synchronization. Two DLTPMs accept the common input and different weight vectors and update the weights using neural learning rules by exchanging their output. In some steps, it results in complete synchronization, and the weights of the two DLTPMs become identical. These identical weights serve as a secret key. There is, however, hardly any research in the field of neural weight vector optimization using a nature-inspired algorithm for faster neural synchronization. In this article, whale optimization-based DLTPM is proposed. For faster synchronization, this proposed DLTPM model uses a whale algorithm optimized weight vector. This proposed DLTPM model is faster and has better security. This proposed technique has been passed through a series of parametric tests. The results have been compared with some recent techniques. The results of the proposed technique have shown effective and has robust potential.

INDEX TERMS Neural synchronization, tree parity machine (TPM), session key, neural network, mutual learning, double layer tree parity machine (DLTPM), whale optimization.

I. INTRODUCTION

A Diffie and Hellman key distribution algorithm [1] is the public-key exchange algorithm. It helps two communication systems to agree on the same encryption key by exchanging a key between them through an insecure medium. In a number of fields such as identification, authentication, data encryption and security, the secret keys are used. Innovative methods for the generation/exchange of cryptographic keys for a secure and low-cost protocol therefore must be required. An attacker E is perhaps unable to deduce the

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secret while he may be able to follow the structure of the algorithm. Chen *et al.* [2]; Liu *et al.* [3]; Chen *et al.* [4]; Wang *et al.* [5], [6]; Xiao *et al.* [7]; Zhang and Cao [8]; Wang *et al.* [9]; Dong *et al.* [10] described that the neural network synchronization approach offers the chance to solve enormous exchange problems. Rosen-Zvi *et al.* [11]; Lakshmanan *et al.* [12]; Ni and Paul [13] recently showed that neural cryptography has the capability of achieving key exchange through neural synchronization of Artificial Neural Networks (ANN).

This proposed technique uses an ANN called the Double Layer Tree Parity Machine (DLTPM). By generating common inputs and sharing the outputs of such networks,

two DLTPM networks of the same configurations will synchronize and keep the synaptic weight secret between them. Two users of A and B will create a cryptographic key that is difficult for the attacker to infer, even though the attacker is aware of the algorithm structure and the communication channel. Since the method of neural synchronization requires less computational power, neural cryptography is suitable for the rapid exchange of information amongst communicators.

The rest of this article is organized accordingly. Section II deals with related works. Section III deals with the proposed methodology. Section IV, and V deal with security analysis and the results respectively. Conclusions and future scopes are given in section VI and references are given at the end.

II. RELATED WORKS

Rosen-Zvi *et al.* [11] and Kanter *et al.* [14] described that upon training two ANNs by a specific learning law, the same states of their internal synaptic weight are successfully developed. Kinzel and Kanter [15] and Ruttor *et al.* [16] identified that if the weight of the network increases, the attack probability decreases and the assailant's computational cost grows exponentially as the user effort becomes polynomial. Sarkar and Mandal [17] and Sarkar *et al.* [18]–[21] proposed schemes to enhance the security of the protocol by improving the synaptic depths of TPM and henceforth counteracting the attacks of the brute strength of the attacker. It is found that the amount of security provided by TPM synchronization can also be improved by inserting a large collection of neurons and entries of each neuron into the hidden layers. Allam *et al.* [22] identified a previously shared secret authentication algorithm. As a result, the algorithm obtains a very high degree of security without increasing synchronization time. Ruttor [23] described that lower values of the hidden unit have negative safety implications. Klimov *et al.* [24] calculated whether or not two networks synchronize their weights. A frequency analysis technique was proposed by Dolecki and Kozera [25] that enables two TPM networks to be evaluated with a defined value that is not related to their differences in synaptic weights before the synchronization steps are completed. Santhanalakshmi *et al.* [26]; Dolecki and Kozera [27] evaluated the efficiency of coordinated usage of genetic algorithm and the Gaussian distribution respectively. As a consequence, the substitution of random weights with optimum weights reduces the synchronization period. The timing distribution of the two TPM networks is adapted from the Poisson distribution by Dolecki and Kozera [27]. Pu *et al.* [28] developed an algorithm that blends “true random sequences” with a TPM network that demonstrates more complex dynamic behaviors that increase the efficiency of encryption and resistance to attacks. According to their study, the synaptic weight values of the TPM networks are generated in a secure, standardized, and distributed. In the light of rules leading to the creation of TPM synchronization, Mu and Liao [29] and Mu *et al.* [30] describes the heuristic of minimum

hamming distances. To test the security level of the final TPM network structure, the hamming distance based heuristic rule was used. Concerning improvements to initial TPM network infrastructure, Gomez *et al.* [31] observed that the synchronization period is reduced from 1.25 ms to less than 0.7 ms with an initial assignment of the weights between 15% to 20%. Niemiec [32] proposed a new concept for the main quantity reconciliation process using TPM networks. Dong and Huang [33] proposed a complex value-based neural network for neural cryptography. Here all the inputs and the outputs are complex value. But, this technique takes a significant amount of time to complete the synchronization process.

The issue of the current key exchange's agreement can be resolved using the proposed technique. This work proposes changes to the TPM framework. The proposed DLTPM approach uses two hidden layers. DLTPMs also take different random weight vectors and share their outputs. For faster synchronization of two DLTPMs, this article proposes optimization of weight vector. This proposed methodology uses a nature-inspired Whale optimization algorithm for weight optimization to reduce the tuning time of two DLTPM networks for generating cryptographic keys for encryption purposes. It results in complete synchronization after certain steps by adjusting weights using traditional rules of learning. In this way, two DLTPMs will generate a cryptographic key that is difficult to guess for the attacker even when the algorithm is known to the attacker. For the study of the proposed method, various parametric tests are performed. Python is used for the implementation of the methodology and R is used for statistical analysis.

III. PROPOSED METHODOLOGY

A. OPTIMAL WEIGHT VECTOR GENERATION ALGORITHM

A whale based optimization [1], [34] is used on the weight values of the DLTPM for faster synchronization. As the optimal weights contribute to faster convergence, a greater weight range can be taken into consideration to enhance the security of existing TPM. Inspiration and foraging behaviors of whales are considered in the whale optimization technique. Whales are the world's largest mammals. Their intelligence is due to the presence of spindle cells in brain. They do live in groups, and they can develop their dialect. They have a special hunting mechanism which is called bubble-net feeding method. This foraging behavior is done by creating a special bubble in a spiral shape. Humpback whales do know the best location of their preys and are encircled. They do consider the current best candidate solution is a best-obtained solution and near to the optimal solution. Once the best candidate solution has been assigned, the other agents try to update their positions in close to the best search agent as shown in the following equations 1 and 2.

$$R = |Q \cdot S^*(itr) - S(itr)| \quad (1)$$

$$S(itr + 1) = S^*(itr) - P \cdot R \quad (2)$$

where present iteration is represented by itr , coefficient vectors are represented by P and Q , position vector of solution and optimal solution is denoted by S and S^* respectively. P and Q are represented as $P = 2x.y.x$ and $Q = 2.y$. Here x and y are random vectors belonging to $[0, 1]$. x 's components are decreasing linearly. Now the helix-shaped movement of the humpback is designed and represented using equation 3.

$$S(itr + 1) = R'.e^{z.m}.cos(2\pi m) + S^*(itr) \quad (3)$$

Here, $R' = |S^*(itr) - S(itr)|$ is the difference between the best and current solution, z is fixed value, m is a random number in the interval $[-1, +1]$. In order to update the positions of the whales, equation 4 is used.

$$S(itr + 1) = \begin{cases} S^*(itr) - P.R & \text{if } n < 0.5 \\ R'.e^{z.m}.cos(2\pi m) + S^*(itr) & \text{if } n \geq 0.5 \end{cases} \quad (4)$$

Here, n is an arbitrary number between 0 and 1. The mathematical model of the exploration phase is given as equation 5 and 6.

$$R = |Q.S_{random} - S| \quad (5)$$

$$S(itr + 1) = S_{random} - P.R \quad (6)$$

Here, the arbitrarily generated position vector is S_{random} which is selected from the current population. The fitness of each whale has been evaluated using the following fitness function given in equation 7.

$$f(S_i^{itr}) = \begin{cases} +\kappa \text{ or } -\kappa & \text{if } S_i^{itr} < -\kappa \text{ or if } S_i^{itr} \geq \kappa \\ \text{weight}^2 & \text{if } -\kappa \leq S_i^{itr} < \kappa \end{cases} \quad (7)$$

Here, κ is the weight range of DLTPM. The population size and the maximum number of iterations considered in this algorithm are 1000 and 100 respectively. The complete process of optimal weight vector generation using whale optimization is illustrated in algorithm 1.

Compared to the various metaheuristics' algorithms, whale optimization has the highest significance in terms of exploitation capability, exploration capacity, ability to get rid of local minima. When evaluated on unimodal functions, whale optimization has a higher exploitation efficiency. It works well on multimodal functions in exploration. Furthermore, checking the optimization of whales on composite functions can be seen as the ideal way to stabilise exploration and exploitation. The optimization of whales has an important exploration potential due to the use of the position updating process of whales. Whales must be arbitrarily shifted around each other in the initial phase of the algorithm. The whales easily update their locations in the next steps and travel down a spiral-shaped path in the direction of the best route that has been discovered so far. Although these two steps are conducted separately and in half iteration each, the optimization of whales prevents local optima and reaches convergence speed across the iterations at the same time.

Algorithm 1

Input: Set the parameters $PopulationSize(sz)$. $Parameter(x)$. $CoefficientVector(P, Q)$. $MaximumIteration(Max_{itr})$.

Output: The best weight vector (whale) for neural synchronization.

Initialisation : counter $itr := 0$.

```

1: for  $i = 1$  to  $i \leq sz$  do
   { /*Initial population of weight vector*/}
2:   Generate an initial population of weight (whale)  $S_i^{itr}$ 
   randomly
3:   Fitness function for each weight (whale) is evaluated
   using  $f(S_i^{itr})$ 
4: end for
5:   Assign the best search agent  $S_i^*(itr)$ 
6: repeat
7:   Set  $itr = itr + 1$ 
8:   for  $i = 1$  to  $i \leq sz$  do
9:     Update  $x, P, Q, m, n$ 
10:    if  $n < 0.5$  then
11:      if  $|P| < 1$  then
12:        Update the current search agent position  $S_i^{itr}$  by
         $S(itr + 1) = S^* - P.R$ 
13:      else
14:        if  $|P| \geq 1$  then
15:          Choose an arbitrary search agent  $S_r(itr)$ 
16:          Update the position of the current search
          agent  $S_i^{itr}$  by  $S(itr + 1) = S_{random} - P.R$ 
17:        end if
18:      end if
19:    else
20:      if  $n \geq 0.5$  then
21:        Update the position of the current search agent
         $S_i^{itr}$  by  $S(itr + 1) = R'.e^{z.m}.cos(2\pi m) + S^*(itr)$ 
22:      end if
23:      Fitness function for each weight (whale) is eval-
      uated by  $f(S_i^{itr})$ 
24:    end if
25:  end for
26:  Replace  $S^*$  with a better solution (if found)
27: until  $itr > Max_{itr}$ 
28: Produce the best solution vector  $S^*$  as optimal weight for
   DLTPM

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It can also be said that whale optimization will improve the speed of convergence during iterations, whereas most optimization algorithms (such as PSO and GSA) do not have operators to dedicate a particular iteration to exploration or exploitation because they use only one format to change the location of search agents. It is fair to assume that whale optimization achieves convergence speed and prevents local optima by iterations at the same time due to the presence of two different phases (exploration and exploitation). In each iteration, all explorations and exploitations are achieved.

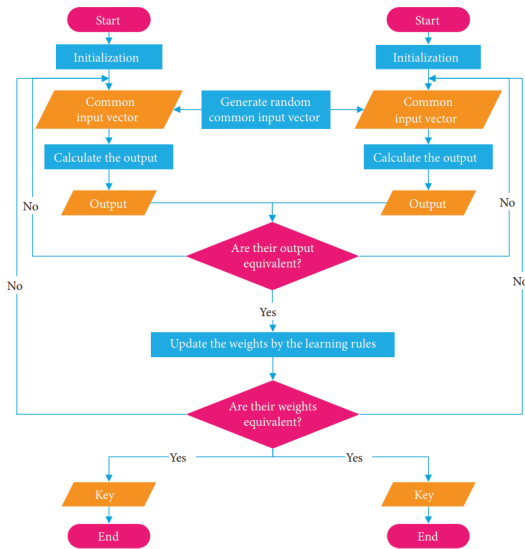


FIGURE 1. Flow diagram of the DLTPM synchronization.

B. DOUBLE LAYER TREE PARITY MACHINES SYNCHRONIZATION

The proposed neural network DLTPM is composed of M no. of input neurons for each H no. of hidden neurons. DLTPM has only one neuron in its output. DLTPM works with binary input, $\alpha_{u,v} \in \{-1, +1\}$. The mapping between input and output is described by the discrete weight value between $-\kappa$ and $+\kappa$, $\beta_{u,v} \in \{-\kappa, -\kappa + 1, \dots, +\kappa\}$.

Figure 1 displays the flow diagram of the DLTPM synchronization and explains each step of it.

- 1) *Step of initialization:* Let us suppose Arindam(A) and Marjit(B) initialize the same parameters of their tree parity unit. Then the weights are generated randomly and their weights are initialized.
- 2) *The phase of estimation:* The identical input vector is obtained by Arindam and Marjit at each learning stage. They calculate the tree parity machines' output and give each other the result.
- 3) *Step of upgrading:* They then evaluate if the two outputs are identical after they obtain another party's output. Arindam and Marjit will adjust the respective weight vector according to basic learning laws. Otherwise, the estimation process will be done.
- 4) *Step of evaluation:* Arindam and Marjit must determine if maximum synchronization is achieved if the weights are updating successfully. The protocol goes into the next step if the complete synchronization is achieved. Otherwise, the estimation process will be done.
- 5) *Finishing process:* Arindam and Marjit are producing their keys by weight. They're finishing the neural key exchange process.

Table 1 lists the variables used in this DLTPM technique.

In DLTPM u -th hidden unit is described by the index $u = 1, \dots, H$ and that of $v = 1, \dots, M$ denotes input neuron corresponding to the u -th hidden neuron of the DLTPM.

TABLE 1. Symbol Description of DLTPM.

Symbol	Description
H	Total number of hidden neurons
M	Total number of input neurons to each hidden neuron
$H1$	Total number of hidden neurons in first hidden layer
$H2$	Total number of hidden neurons in second hidden layer
κ	Weight range
ζ	Final output of the DLTPM
Q_u	The normalized overlap
ρ_u	The normalized overlap
h_u	u -th hidden unit's local field
$pb_{a,b}^u$	The likelihood distribution of the weight values in u -th hidden neuron of a's and b's DLTPM
S	Weight's entropy
α_u	The input vector of the u -th hidden unit
β_u	The weight vector of the u -th hidden unit
$\alpha_{u,v}$	v -th element of α_u
$\beta_{u,v}$	v -th element of β_u
γ_u	u -th hidden unit's output

Consider there are $H1, H2$ numbers of hidden units in the first and second hidden layers respectively. Each hidden unit of the first layer calculates its output by performing the weighted sum over the present state of inputs on that particular hidden unit. Similarly, each hidden unit of the second layer calculates its output by performing the weighted sum over the hidden units of first layer on that particular hidden unit. The calculation for the first hidden layer is given by equation 8.

$$\begin{aligned}
 h_u &= \frac{1}{\sqrt{M}} \alpha_u \cdot \beta_u \\
 &= \frac{1}{\sqrt{M}} \sum_{v=1}^M \alpha_{u,v} \beta_{u,v}
 \end{aligned}
 \tag{8}$$

$sigum(h_u)$ define the output γ_u of the u -th hidden unit. (in equation 9),

$$\gamma_u = sigum(h_u)
 \tag{9}$$

If $h_u = 0$ then γ_u is set to -1 to make the output in binary form. If $h_u > 0$ then γ_u is mapped to $+1$, which represents that the hidden unit is active. If $\gamma_u = -1$ then it denotes that the hidden unit is inactive (in equation 10).

$$sigum(h_u) = \begin{cases} -1 & \text{if } h_u \leq 0 \\ +1 & \text{if } h_u > 0 \end{cases}
 \tag{10}$$

The product of the hidden neurons of the third layer denotes the ultimate result of DLTPM. This is represented by ζ is (in equation 11),

$$\zeta = \prod_{u=1}^{H2} \gamma_u
 \tag{11}$$

The value of ζ is mapped in the following way (in equation 12),

$$\zeta = \begin{cases} -1 & \text{if } \gamma_u = -1, \text{ is odd} \\ +1 & \text{if } \gamma_u = -1, \text{ is even} \end{cases}
 \tag{12}$$

$\zeta = \gamma_1$, if only one hidden unit ($H = 1$) is there. ζ value can be the same for 2^{H-1} different $(\gamma_1, \gamma_2, \dots, \gamma_H)$ representations.

If the output of two parties disagrees, $\zeta^A \neq \zeta^B$, then no update is allowed on the weights. Otherwise, follow the following rules:

TPM be trained from each other using Hebbian learning rule [15] (in equation 13).

$$\beta_{u,v}^+ = fn(\beta_{u,v} + \alpha_{u,v}\zeta\Theta(\gamma_u\zeta)\Theta(\zeta^A\zeta^B)) \quad (13)$$

In the Anti-Hebbian learning rule, both TPM is learned with the reverse of their output [15] (in equation 14).

$$\beta_{u,v}^+ = fn(\beta_{u,v} - \alpha_{u,v}\zeta\Theta(\gamma_u\zeta)\Theta(\zeta^A\zeta^B)) \quad (14)$$

If the set value of the output is not imperative for tuning given that it is similar for all participating TPM then random-walk learning rule, is used (in equation 15).

$$\beta_{u,v}^+ = fn(\beta_{u,v} + \alpha_{u,v}\Theta(\gamma_u\zeta)\Theta(\zeta^A\zeta^B)) \quad (15)$$

If $X = Y$ then $\Theta(X, Y) = 1$ Otherwise, if $X \neq Y$ then $\Theta(X, Y) = 0$. Only weights are updated which are in hidden units with $\gamma_u = \zeta$. $fn(\beta)$ is used for each learning rule (in equation 16).

$$fn(\beta) = \begin{cases} \text{signum}(\beta)\kappa & \text{for } |\beta| > \kappa \\ \beta & \text{otherwise} \end{cases} \quad (16)$$

The likelihood distribution of the weight values in u -th hidden neuron of two DLTPM is represented by $(2\kappa + 1)$ (in equation 17).

$$pb_{a,b}^u = P(\beta_{u,v}^A = a \wedge \beta_{u,v}^B = b) \quad (17)$$

The standard order parameters [35] can be calculated as functions of $pb_{a,b}^u$ shown in equation 18, 19, and 20.

$$Q_u^A = \frac{1}{M}\beta_U^A\beta_U^A = \sum_{a=-\kappa}^{\kappa} \sum_{b=-\kappa}^{\kappa} a^2 pb_{a,b}^u \quad (18)$$

$$Q_u^B = \frac{1}{M}\beta_U^B\beta_U^B = \sum_{a=-\kappa}^{\kappa} \sum_{b=-\kappa}^{\kappa} b^2 pb_{a,b}^u \quad (19)$$

$$Q_u^{AB} = \frac{1}{M}\beta_U^A\beta_U^B = \sum_{a=-\kappa}^{\kappa} \sum_{b=-\kappa}^{\kappa} ab pb_{a,b}^u \quad (20)$$

Tuning is represented by the normalized overlap [35] given in equation 21.

$$\rho_u^{AB} = \frac{\beta_u^A \beta_u^B}{\sqrt{\beta_u^A \cdot \beta_u^A} \sqrt{\beta_u^B \cdot \beta_u^B}} = \frac{R_u^{AB}}{\sqrt{Q_u^A \cdot Q_u^B}} \quad (21)$$

Calculate the entropy [36] using equation 22.

$$S_u^{AB} = -M \sum_{a=-\kappa}^{\kappa} \sum_{b=-\kappa}^{\kappa} pb_{a,b}^u \ln pb_{a,b}^u \quad (22)$$

The weight's entropy in a single hidden neuron is represented by equations 23 and 24.

$$S_u^A = -M \sum_{a=-\kappa}^{\kappa} \left(\sum_{b=-\kappa}^{\kappa} pb_{a,b}^u \right) \ln \left(\sum_{b=-\kappa}^{\kappa} pb_{a,b}^u \right) \quad (23)$$

$$S_u^B = -M \sum_{b=-\kappa}^{\kappa} \left(\sum_{a=-\kappa}^{\kappa} pb_{a,b}^u \right) \ln \left(\sum_{a=-\kappa}^{\kappa} pb_{a,b}^u \right) \quad (24)$$

Using equations 22, 23, and 24 the common information [36] of A's and B's represented using equation 25.

$$In^{AB} = \sum_{u=1}^H (S_u^A + S_u^B - S_u^{AB}) \quad (25)$$

The likelihood to observe $\gamma_u\alpha_{u,v} = +1$ or $\gamma_u\alpha_{u,v} = -1$ are not equal, but depend on the related weight $\beta_{u,v}$ (in equation 26).

$$P(\gamma_u\alpha_{u,v} = 1) = \frac{1}{2} \left(1 + \text{erf} \left(\frac{\beta_{u,v}}{\sqrt{MQ_u - \beta_{u,v}^2}} \right) \right) \quad (26)$$

$\gamma_u\alpha_{u,v} = \text{signum}(\beta_{u,v})$ occurs more frequently than $\gamma_u\alpha_{u,v} = -\text{signum}(\beta_{u,v})$, the stationary likelihood distribution of the weights for $t \rightarrow \infty$, is computed using equation 19 for the transition likelihood [16]. This is represented using equation 27.

$$P(\beta_{u,v} = \beta) = p_0 \prod_{i=1}^{|\beta|} \frac{1 + \text{erf} \left(\frac{i-1}{\sqrt{MQ_u - (i-1)^2}} \right)}{1 - \text{erf} \left(\frac{i}{\sqrt{MQ_u - i^2}} \right)} \quad (27)$$

Here the normalization constant p_0 is given by equation 28.

$$p_0 = \left(\sum_{\beta=-\kappa}^{\kappa} \prod_{i=1}^{|\beta|} \frac{1 + \text{erf} \left(\frac{i-1}{\sqrt{MQ_u - (i-1)^2}} \right)}{1 - \text{erf} \left(\frac{i}{\sqrt{MQ_u - i^2}} \right)} \right)^{-1} \quad (28)$$

For $M \rightarrow \infty$, the parameter of the error functions will not be considered so that the weights remain consistent as shown in equation 29.

$$\sqrt{Q_u(t=0)} = \sqrt{\frac{\kappa(\kappa+1)}{3}} \quad (29)$$

Otherwise, if M is finite, the likelihood distribution represented using order parameter Q_u will be as shown in equation 30.

$$Q_u = \sum_{\beta=-\kappa}^{\kappa} \beta^2 P(\beta_{u,v} = \beta) \quad (30)$$

Intensifying it in terms of $M^{-1/2}$ results in equation 31.

$$Q_u = \frac{\kappa(\kappa+1)}{3} + \frac{8\kappa^4 + 16\kappa^3 - 10\kappa^2 - 18\kappa + 9}{15\sqrt{3\pi\kappa(\kappa+1)}} \frac{1}{\sqrt{M}} + O\left(\frac{\kappa^4}{M}\right) \quad (31)$$

In the case of $1 \ll \kappa \ll \sqrt{M}$, the asymptotic performance of the order parameter is represented using equation 32.

$$Q_u \sim \frac{\kappa(\kappa + 1)}{3} \left(1 + \frac{8}{5\sqrt{3\pi}} \frac{\kappa}{\sqrt{M}} \right) \quad (32)$$

First-order approximation of Q_u is given by equation 33.

$$Q_u = \frac{\kappa(\kappa + 1)}{3} - \frac{8\kappa^4 + 16\kappa^3 - 10\kappa^2 - 18\kappa + 9}{15\sqrt{3\pi\kappa(\kappa + 1)}} \frac{1}{\sqrt{M}} + O\left(\frac{\kappa^4}{M}\right) \quad (33)$$

This systematically converges to equation 34.

$$Q_u \sim \frac{\kappa(\kappa + 1)}{3} \left(1 - \frac{8}{5\sqrt{3\pi}} \frac{\kappa}{\sqrt{M}} \right) \quad (34)$$

If $\zeta^A = \zeta^B$, but $\gamma_u^A \neq \gamma_u^B$, the weight of one hidden neuron is changed. The weights execute an anisotropic diffusion in case of attractive steps that takes to equation 35.

$$pb_{a,b}^{u+} = \frac{1}{2} (pb_{a+1,b+1}^u + pb_{a-1,b-1}^u) \quad (35)$$

Repulsive steps, as an alternative, are equal to normal diffusion steps (in equation 36)

$$pb_{a,b}^{u+} = \frac{1}{4} (pb_{a+1,b}^u + pb_{a-1,b}^u + pb_{a,b+1}^u + pb_{a,b-1}^u) \quad (36)$$

on the same lattice. $\Delta\rho_{s_{attr}}(\rho)$ and $\Delta\rho_{s_{repu}}(\rho)$ are random variables. $\Delta\rho_{s_{attr}}$ and $\Delta\rho_{s_{repu}}$ are the step size for attractive and repulsive respectively as shown in equations 37 and 38.

$$\Delta\rho_{s_{attr}} = \frac{3}{\kappa(\kappa + 1)} \left(1 - \sum_{v=-\kappa}^{+\kappa} (2v + 2) pb_{\kappa,v} + pb_{\kappa,\kappa} \right) \quad (37)$$

$$\Delta\rho_{s_{repu}} = -\frac{3}{\kappa(\kappa + 1)} \left(\sum_{v=-\kappa}^{+\kappa} \frac{v}{2} (pb_{\kappa,j} - pb_{-\kappa,v}) \right) \quad (38)$$

At the initial state of the synchronization, it has its highest effect (in equation 39),

$$\Delta\rho_{s_{attr}}(\rho = 0) = \frac{12\kappa}{(\kappa + 1)(2\kappa + 1)^2} \sim \frac{3}{\kappa^2} \quad (39)$$

Weights are uncorrelated as shown in equation 40.

$$pb_{a,b}(\rho = 0) = \frac{1}{(2\kappa + 1)^2} \quad (40)$$

Highest consequence (in equation 41)

$$\Delta\rho_{s_{repu}}(\rho = 1) = \frac{3}{(\kappa + 1)(2\kappa + 1)} \sim -\frac{3}{2\kappa^2} \quad (41)$$

is achieved for complete harmonized weights (in equation 42).

$$pb_{a,b}(\rho = 1) = \begin{cases} (2\kappa + 1)^{-1} & \text{for } a = b \\ 0 & \text{for } a \neq b \end{cases} \quad (42)$$

The weights are updated if $\zeta^A = \zeta^B$. ϵ_u is the generalization error. In common overlap for H hidden neurons, $\epsilon_u = \epsilon$, the likelihood is represented using equation 43.

$$Pb_{id} = Pb(\zeta^A = \zeta^B) = \sum_{u=0}^{H/2} \left(\frac{H}{2u} \right) (1 - \epsilon)^{H-2u} \epsilon^{2u} \quad (43)$$

For synchronization of DLTPM with $H > 1$, the likelihood of attractive as well as repulsive are represented using by equations 44 and 45.

$$Pb_{attr}^B = \frac{1}{2Pb_{id}} \sum_{u=0}^{\left(\frac{H-1}{2}\right)} \left(\frac{H-1}{2u} \right) (1 - \epsilon)^{H-2u} \epsilon^{2u} \quad (44)$$

$$Pb_{repu}^B = \frac{1}{Pb_{id}} \sum_{u=1}^{H/2} \left(\frac{H-1}{2u-1} \right) (1 - \epsilon)^{H-2u} \epsilon^{2u} \quad (45)$$

For $H = 3$, this leads to equations 46 and 47.

$$Pb_{attr}^B = \frac{1}{2} \frac{(1 - \epsilon)^3 + (1 - \epsilon)\epsilon^2}{(1 - \epsilon)^3 + 3(1 - \epsilon)\epsilon^2} \quad (46)$$

$$Pb_{repu}^B = \frac{2(1 - \epsilon)\epsilon^2}{(1 - \epsilon)^3 + 3(1 - \epsilon)\epsilon^2} \quad (47)$$

Harmonization time $Tm_{r,s}$ for the two random walk beginning at position s and distance r , $Rf_{r,s}$ is the time of the first reflection. $Tm_{r,s}$ is given by equation 48.

$$Tm_{r,s} = Rf_{r,s} + \sum_{v=1}^{r-1} Rf_{v,1} \quad (48)$$

Replacing equation 41 with equation 48 leads to equation 49.

$$\langle Tm_{r,s} \rangle = \langle m - r + 1 \rangle s - s^2 + \frac{1}{2}(r - 1)(2m - r) \quad (49)$$

Tuning time Tm for arbitrarily selected beginning positions of the 2 random walks represented using equations 50 and 51.

$$\begin{aligned} \langle Tm \rangle &= \frac{2}{m^2} \sum_{r=1}^{m-1} \sum_{s=1}^{m-r} \langle Tm_{r,s} \rangle \\ &= \frac{(m-1)^2}{3} + \frac{(m-1)}{3m} \end{aligned} \quad (50)$$

$$\begin{aligned} \langle Tm^2 \rangle &= \frac{2}{m^2} \sum_{r=1}^{m-1} \sum_{s=1}^{m-r} \langle Tm_{r,s}^2 \rangle \\ &= \frac{(17m^5 - 51m^4 + 65m^3 - 45m^2 + 8m + 6)}{90m} \end{aligned} \quad (51)$$

The mean attractive steps needed to achieve a harmonized state increases nearly proportional to m^2 (equation 52).

$$\langle Tm \rangle \sim \frac{1}{3m^2} \sim \frac{4}{3\kappa^2} \quad (52)$$

This result is fixed with the scaling performance $\langle tm_{synch} \rangle \propto \kappa^2$ found for TPM harmonization.

The standard deviation of Tm is shown in equation 53.

$$SD_{Tm} = \sqrt{\frac{(7m^6 - 11m^5 - 15m^4 + 55m^3 - 72m^2 + 46m - 10)}{90m^2}} \quad (53)$$

Here, system size $m = 2\kappa + 1$. SD_{Tm} is proportional asymptotically to $\langle Tm \rangle$ (equation 54).

$$SD_{Tm} \sim \sqrt{\frac{7}{10}} \langle Tm \rangle \quad (54)$$

IV. SECURITY ANALYSIS

A. GEOMETRIC ATTACK

In this proposed technique a geometric attack is considered on DLTPM. The likelihood of $\gamma_u^E \neq \gamma_u^A$ is represented using the prediction error [37] using equation 55,

$$\varepsilon_u^p = \frac{1}{2} \left[1 - \operatorname{erf} \left(\frac{\rho_u}{\sqrt{2(1 - \rho_u^2)}} \frac{|h_u|}{\sqrt{Q_u}} \right) \right] \quad (55)$$

of the perceptron. When the u -th hidden neuron does not agree and rest of all hidden units has a condition of $\gamma_v^E \neq \gamma_v^A$, then the likelihood of a modification using the geometric attack is shown using equation 56.

$$P_k^+ = \int_0^\infty \left(\frac{2}{\sqrt{2\pi Q}} \right)^H \left(\int_{h_u}^\infty \frac{1 - \epsilon^P(h)}{1 - \epsilon} e^{-\frac{h^2}{2Q}} dh \right)^{H-k} \times \left(\int_{h_u}^\infty \frac{\epsilon^P(h)}{\epsilon} e^{-\frac{h^2}{2Q}} dh \right)^{k-1} \frac{\epsilon^P(h_u)}{\epsilon} e^{-\frac{h_u^2}{2Q}} dh_u \quad (56)$$

For identical order parameters $Q = Q_v^E$ and $R = R_j^{AE}$ and various outputs $\gamma_v^A \neq \gamma_v^E$. Then the likelihood for a modification of $\gamma_u^E \neq \gamma_u^A$ is shown using equation 57.

$$P_k^+ = \int_0^\infty \left(\frac{2}{\sqrt{2\pi Q}} \right)^H \left(\int_{h_u}^\infty \frac{1 - \epsilon^P(h)}{1 - \epsilon} e^{-\frac{h^2}{2Q}} dh \right)^{H-k} \times \left(\int_{h_u}^\infty \frac{\epsilon^P(h)}{\epsilon} e^{-\frac{h^2}{2Q}} dh \right)^{k-1} \frac{\epsilon^P(h_u)}{\epsilon} e^{-\frac{h_u^2}{2Q}} dh_u \quad (57)$$

Using the same equation the likelihood for an incorrect modification of $\gamma_u^E = \gamma_u^A$ is shown with the help of equation 58.

$$P_k^- = \int_0^\infty \left(\frac{2}{\sqrt{2\pi Q}} \right)^K \left(\int_{h_i}^\infty \frac{1 - \epsilon^P(h)}{1 - \epsilon} e^{-\frac{h^2}{2Q}} dh \right)^{K-k-1} \times \left(\int_{h_i}^\infty \frac{\epsilon^P(h)}{\epsilon} e^{-\frac{h^2}{2Q}} dh \right)^k \frac{1 - \epsilon^P(h_u)}{1 - \epsilon} e^{-\frac{h_u^2}{2Q}} dh_u \quad (58)$$

$\gamma_u^E \neq \gamma_u^A$ condition is satisfied and in total there is an even number of hidden units that satisfied this condition then no geometric modification is done. Equation 59 represents this.

$$P_{r,1}^E = \sum_{u=1}^{H/2} \left(\frac{H-1}{2u-1} \right) (1 - \epsilon)^{H-2u} \epsilon^{2u} \quad (59)$$

Second part of P_r^E can be represented using equation 60.

$$P_{r,2}^E = \sum_{u=1}^{H/2} \left(\frac{H-1}{2u-1} \right) P_{2u-1}^- (1 - \epsilon)^{H-2u+1} \epsilon^{2u-1} \quad (60)$$

Third part of P_r^E can be represented using equation 61.

$$P_{r,3}^E = \sum_{u=1}^{(H-1)/2} \left(\frac{H-1}{2u} \right) (1 - P_{2u+1}^+) (1 - \epsilon)^{-2u-1} \epsilon^{2u+1} \quad (61)$$

If $H > 1$ then the probability value of attractive steps and repulsive steps in the u -th hidden unit are represented using equations 62 and 63.

$$P_a^E = \frac{1}{2} \left(1 - \sum_{v=1}^3 P_{r,v}^E \right) \quad (62)$$

$$P_r^E = \sum_{v=1}^3 P_{r,v}^E \quad (63)$$

Attractive steps are performed when $H = 1$. If $H = 3$ probability value can be calculated using equation 56, that forms equation 64 and 65.

$$P_a^E = \frac{1}{2} (1 + 2P_g) (1 - \epsilon)^2 \epsilon + \frac{1}{2} (1 - \epsilon)^3 + \frac{1}{2} (1 - \epsilon)^2 + \frac{1}{6} \epsilon^3 \quad (64)$$

$$P_r^E = 2(1 - P_g) (1 - \epsilon)^2 \epsilon + 2(1 - \epsilon) \epsilon^2 + \frac{2}{3} \epsilon^3 \quad (65)$$

B. SECRET KEY SPACE ANALYSIS

Consider n number of cascading encryption/decryption technique is used to encrypt/decrypt the plaintext with the help of neural synchronized session key. Then a session key of length [(number of cascaded encryption technique in bits) + (three bits combinations of encryption/ decryption technique index) + (length of n number of encryption/decryption keys in bits) + (length of n number of session keys in bits)] i.e. [8 + (3 × n) + (128 × n) + (128 × n)] bits to [8 + (3 × n) + (256 × n) + (256 × n)] number of bits. So,

$$\frac{[8 + (3 \times n) + (128 \times n) + (128 \times n)]}{8} = \left[1 + \frac{(3 \times n)}{8} + 16n + 16n \right] = 32n \text{ to } \frac{[8 + (3 \times n) + (256 \times n) + (256 \times n)]}{8} = \left[1 + \frac{(3 \times n)}{8} + 32n + 32n \right]$$

= 64n numbers of characters.

Therefore, the total number of keys = 256^{64n} . Attacker checks with half of the possible keys on an average, the time needed at 1 decryption/ $\mu s = 0.5 \times 256^{64n} \mu s = 0.5 \times 2^{8 \times 64n} \mu s = 0.5 \times 2^{512n} \mu s = 2^{(512n-1)} \mu s$.

Consider any single encryption using the neural key of size 512 bits which is hypothetically approved and needed to be analyzed in the context of the time taken to crack a ciphertext with the help of the fastest supercomputers available at present. In this neural technique to crack a ciphertext, the number of permutation combinations on the neural key is $2^{512} = 1.340780 \times 10^{154}$ trials for a size of 512 bits only. IBM Summit at Oak Ridge, U.S. invented the fastest supercomputer in the world with 148.6 PFLOPS i.e. means 148.6×10^{15} floating-point computing/second. Certainly, it can be considered that each trial may require 1, 000 FLOPS to undergo its operations. Hence, the total test

TABLE 2. Time Taken for Brute Force Attack.

n	Key Space	Brute Force attack time using IBM Summit Supercomputer at Oak Ridge with a speed of 148.6 PFLOPS
1	$256^{64 \times 1} = 2^{512}$	2.86109×10^{132} years
2	$256^{64 \times 2} = 2^{1024}$	3.83610×10^{286} years
3	$256^{64 \times 3} = 2^{1536}$	5.14337×10^{440} years
4	$256^{64 \times 4} = 2^{2048}$	6.89613×10^{594} years
5	$256^{64 \times 5} = 2^{2560}$	9.24620×10^{748} years
6	$256^{64 \times 6} = 2^{3072}$	1.23971×10^{903} years
7	$256^{64 \times 7} = 2^{3584}$	1.66218×10^{1057} years
8	$256^{64 \times 8} = 2^{4096}$	2.22862×10^{1211} years

TABLE 3. Comparison of p_Value Between Proposed DLTPM and the Existing CVTPM.

NIST Test	p_Value of Proposed DLTPM	p_Value of CVTPM [33]
Frequency	0.572896	0.512374
Frequency within a Block	0.560235	0.538721
Runs	0.526750	0.489451
Longest Run of Ones in a Block	0.096128	0.042081
Binary Matrix Rank	0.651278	0.417393
Discrete Fourier Transform	0.405736	0.392762
Non-overlapping Template Matching	0.451278	0.431759
Overlapping (Periodic) Template Matching	0.201957	0.170426
Maurer’s “Universal Statistical”	0.765192	0.689478
Linear Complexity	0.634265	0.594917
Serial	0.504568	0.478902
Approximate Entropy	0.263472	0.204175
Cummulative Sums	0.679248	0.587290
Random Excursions	0.319684	0.299875
Random Excursions Variants	0.213586	0.180542

needed per second is 148.6×10^{12} . No. of seconds in a year = $365 \times 24 \times 60 \times 60 = 31,536,000$ sec. Total number of years for Brute Force attack: $(1.340780 \times 10^{154}) / (148.6 \times 10^{12} \times 31,536,000) = 2.86109 \times 10^{132}$ years. Table 2 shows how much time is involved for the brute force attack using IBM Summit Supercomputer at Oak Ridge with a speed of 148.6 PFLOPS.

V. RESULTS AND ANALYSIS

For results and simulation purposes, the Intel Core i7 10th Generation processor, 2.6 GHz, 16 GB RAM is used. In the proposed transmission technique, true randomness is assured by qualifying the fifteen tests found in the NIST statistical tests [38] suite. For such a proposed approach with elevated robustness, these tests are very useful. The acceptance or rejection of the input vector is determined by a probability value (p-Value). Table 3 contains the results of NIST statistical tests [38] on the generated random input vector. The p-Value comparison between the proposed and the existing CVTPM(Complex Valued TPM) system is also present in this table [33]. From the table, it was shown that the p-Value of the proposed technique surpassed CVTPM in the NIST statistical test.

The result of the frequency test indicates a ratio of 0 and 1 in the generated random sequence. Here, the value of the

TABLE 4. Comparison of p_Value of NIST Frequency Test.

Technique	p_Value of NIST Frequency Test
Proposed DLTPM	0.572896
CVTPM [33]	0.512374
Karakaya et al. [40]	0.1329
Patidar et al. [41]	0.632558
Liu et al. [42]	0.629806

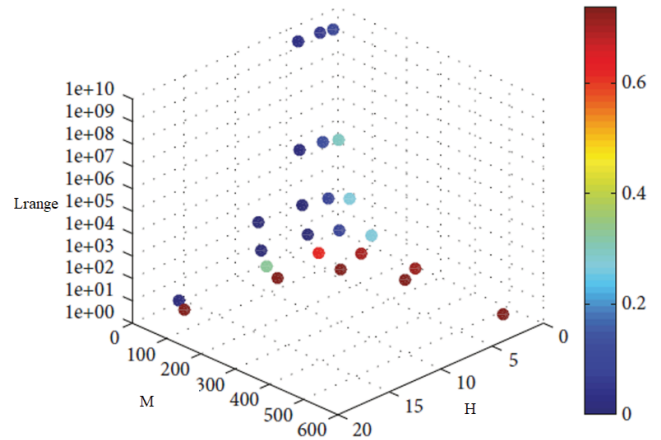


FIGURE 2. Shows how the probabilities differ with H1 – H2 – M – κ values.

frequency test is 0.572896 which is quite average [39] and better than the result of frequency test 0.1329 in [40], and 0.632558 in [41] 0.629806 in [42]. A comparison of p_Value of NIST frequency test is given in Table 4.

The results of different H1 – H2 – M – κ simulations are shown in Table 5. The number of minimum and maximum synchronization steps shows several minimum and maximum steps to synchronize the weights of the two networks. The column for the average steps represents the sum of all the simulations performed. The minimum and maximum time synchronization columns shall signify the minimum and maximum time in seconds needed to synchronize the weights of the two networks. Effective synchronization of the attacker column E reveals how many times the attacking network has been imitating the actions of the other two networks for complete simulations. Finally, the percentage of effective synchronization of the attacker column E (%) successfully indicates the percentage of total simulations shown in the previous column.

As shown in Table 5, the combinations (8-8-16-8) and (8-8-8-128), respectively, are the best results for defense against the attacking network. E did not mimic the actions of A and B’s DLTPM in any of the 500,000 simulations. The best combination of values for the trio was determined from Table 6 (8-8-16-8).

This is evaluated from Table 5 that the success probability of the attacking network depends on the H1 – H2 – M – κ combination. With all possible combinations, their respective probabilities have been established. Using the Octave GNU scatter3 function, a scatter diagram was drawn to do this.

TABLE 5. Results After 500,000 Simulations With Different Values of $H1 - H2 - M - \kappa$.

$H1 - H2 - M - \kappa$	No. of Min Sync. Steps	No. of Max Sync. Steps	Min Sync. time (sec.)	Max Sync. time (sec.)	Successful % of Sync. of Attacker E	Successful % of Sync. of Attacker E (%)
(1-1-1-512-1)	8	34	0.0729	3.4398	358976	71.795
(2-2-2-256-1)	10	30	0.0698	2.6739	356757	71.351
(4-4-4-128-1)	10	39	0.0810	3.1908	358768	71.753
(8-8-8-64-1)	8	26	0.0749	2.8183	357862	71.572
(1-1-1-256-2)	9	45	0.0702	2.9652	358965	71.793
(2-2-2-128-2)	10	35	0.0686	621.8954338978	67.795	
(4-4-4-64-2)	10	234	0.0719	108.7835310878	62.175	
(8-8-8-32-2)	11	973	0.0628	32.7614	117894	23.578
(1-1-1-128-8)	14	87	0.0643	1.9856	119089	23.817
(2-2-2-64-8)	18	510	0.0698	3.3908	39796	7.959
(4-4-4-32-8)	25	820	0.0520	6.2578	208	0.0416
(8-8-8-16-8)	41	749	0.0346	0.0711	0	0.0
(1-1-1-64-128)	10	118	0.0268	0.7658	138678	27.735
(2-2-2-32-128)	17	428	0.0513	3.3679	35726	7.1452
(4-4-4-16-128)	26	930	0.0386	3.8674	593	0.1186
(8-8-8-128)	39	1078	0.0517	5.1786	0	0.0

TABLE 6. Results After 1000,000 Simulations for the (8-8-16-8) and (8-8-8-128) Combinations.

$H1 - H2 - M - \kappa$	No. of Min Sync. Steps	No. of Max Sync. Steps	Min Sync. time (sec.)	Max Sync. time (sec.)	Successful % of Sync. of Attacker E	Successful % of Sync. of Attacker E (%)
(8-8-16-8)	42	820	0.0825	2.5840	0	0
(8-8-8-128)	32	897	0.0395	0.9734	2	0.0002

The proposed approach starts with values like $H1 - H2 - M - \kappa$ and the probability of the attacker’s success in any combination. By using a different combination of $H1 - H2 - M - \kappa$ values, we then draw a 3D dispersion diagram. The scale of each point plotted here is 16. The probabilities describe the likelihood value of each color dot (see Figure 2). To enhance visualization, the Z-axis (κ) scale to a logarithmic one. The *xlabel*, *ylabel* and *zlabel* are assigned to their corresponding values $H1 - H2 - M - \kappa$ respectively. Figure 2 shows how the probabilities differ with a different combination of $H1 - H2 - M - \kappa$ values. Each point

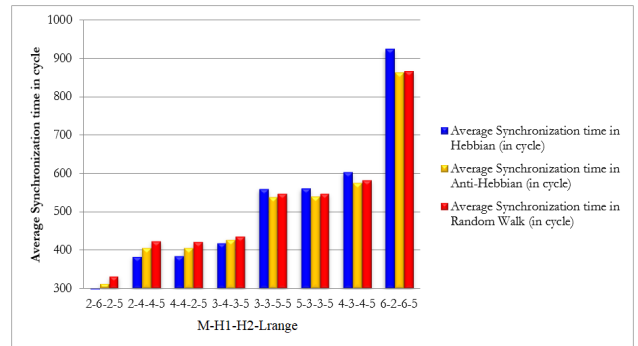


FIGURE 3. 128-bit session key generation with variable DLTPM architecture and fixed synaptic depth.

color displays the attacking network’s probability of success. Good is a small likelihood (Blue), while bad is a high probability (Red). The value of hidden neuron influences probability greatly, shown in figure 2. A high value of M and a very small value of (κ) has an adverse impact. Therefore, a fairly low value of M is suggested for proposing values of $H1 - H2 - M - \kappa$, but M value must be higher than hidden neuron value. (κ) value shouldn’t be too low. It means that a successful passive assault is quite unlikely.

Figure 3 shows that several DLTPM configurations (in terms of different neurons in different layers) can be used to generate a 128-bit session key with a fixed weight range (κ) = 5. Weight value acts as a key to the session. Among the three learning rules, Hebbian rules outperform two other rules when the network size is small.

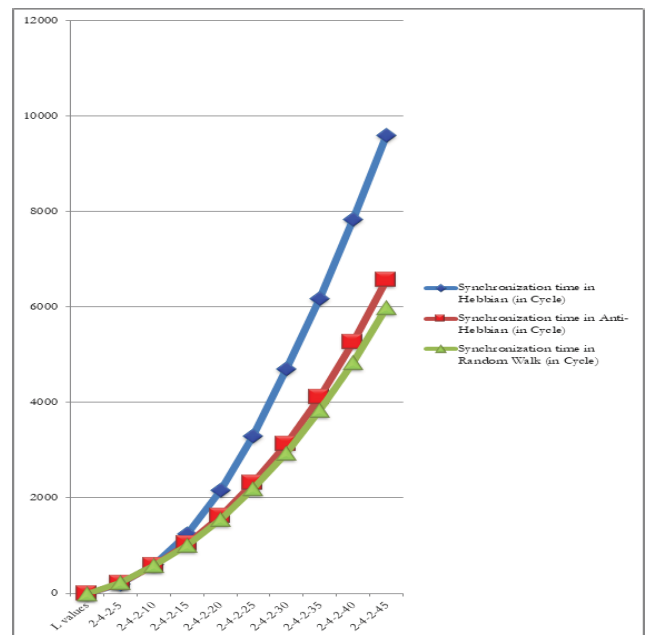


FIGURE 4. Generation of 256-bit session key using different weight Range to and fixed number of neurons in input and hidden layer.

In the following Figure 4, the graph shows a trend towards increase in the synchronization steps as the range for weight range κ increases for a fixed number of neurons in input and

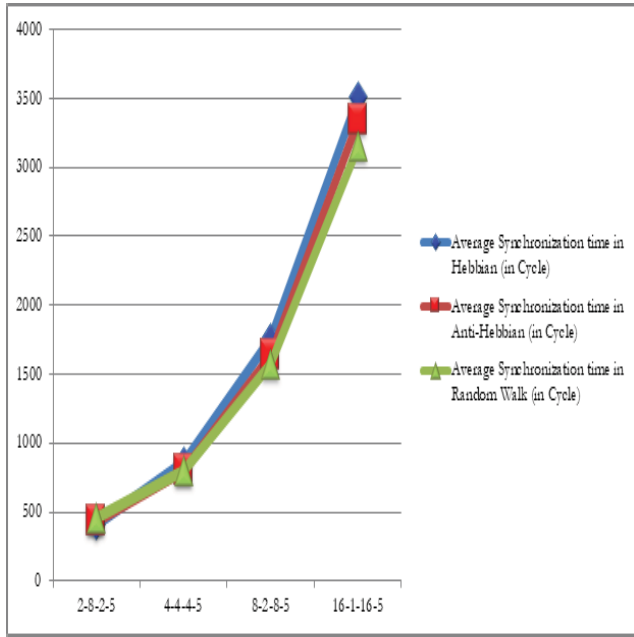


FIGURE 5. Generation of 512-bit session key using fixed $\kappa = 5$ and different number of neurons in input and hidden layer.

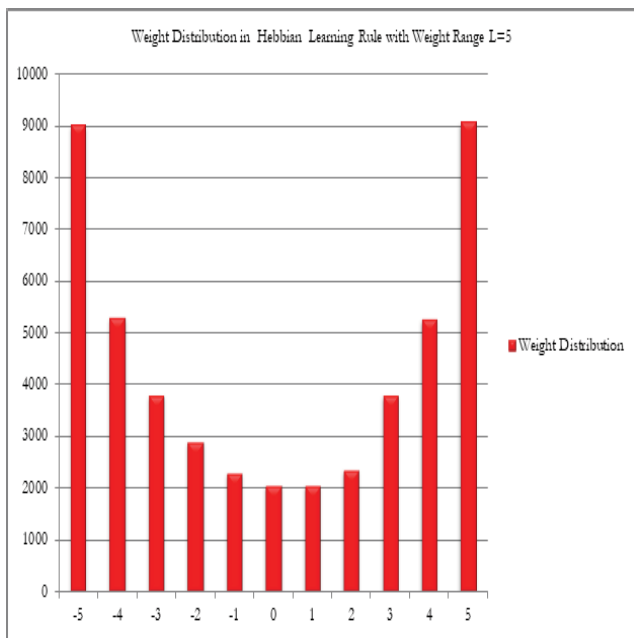


FIGURE 6. Weight distribution in Hebbian learning rule with weight range $\kappa = 5$.

hidden layers in all three learning rules for generation of a session key of 256-bit. For small κ values Hebbian takes less synchronization steps than other two learning rules in the range of 2-4-2-5 to 2-4-2-15 but as the κ value increases Hebbian rule takes more steps to synchronize than other two learning rules. Here, Anti-Hebbian rules take less time than Hebbian and Random Walk learning rules in the range of 2-4-2-20 to 2-4-2-30. Random Walk outperforms from

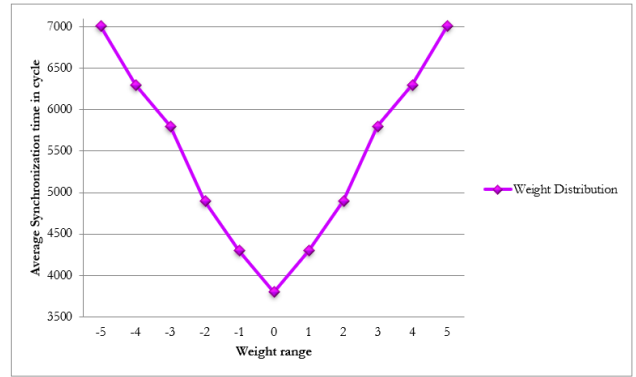


FIGURE 7. Weight distribution in random walk learning rule with weight range $\kappa = 5$.

TABLE 7. Comparison of Synchronization Time for Fixed Network Size and Variable Learning Rules and Synaptic Depth in Proposed DLTPM and Existing CVTPM Method.

κ Value	Sync. time in Hebbian Learning Rule (in Cycle) in Proposed DLTPM	Sync. time in Anti-Hebbian Learning Rule (in Cycle) in Proposed DLTPM	Sync. time in Random Walk Learning Rule (in Cycle) in Proposed DLTPM	Sync. time in Hebbian Learning Rule (in Cycle) in Existing CVTPM [33]	Sync. time in Hebbian Learning Rule (in Cycle) in Existing CVTPM [33]	Sync. time in Random Walk Learning Rule (in Cycle) in Existing CVTPM [33]
5	287,81	309,23	320,52	348,16	389,26	415,63
10	664,59	682,25	675,47	813,64	753,09	713,94
15	1356,06	1136,92	1104,92	1769,57	1198,47	1104,81
20	2271,32	1703,26	1648,13	2971,04	1857,24	1696,35
25	3407,18	2411,15	2302,83	4186,59	2671,17	2540,62
30	4836,97	3220,86	3074,10	5982,41	3582,75	3318,49
35	6319,72	4192,53	3959,65	7310,37	4793,62	4518,27
40	7987,63	5341,28	4978,72	8953,50	5981,43	5372,11
45	9753,02	6662,07	6147,49	11207,26	8138,39	7363,29
50	12980,17	8137,47	7423,34	14952,38	9452,57	8720,93

2-4-2-35 and beyond that. The most vital findings is that if the synaptic depth i.e. weight range κ is increased, the complexity of a successful attack grows exponentially, but there is only a polynomial increase of the effort needed to generate a key. So, increasing the κ value security of the system can be increased.

Figure 5 shows the synchronization time needed for different DLTPM configurations with a fixed weight range $\kappa = 5$. It shows the comparisons of synchronization time to generate the 512-bit session key using fixed $\kappa = 5$ and different number of neurons in input and hidden layers. Among the three learning rules, here also it is observed that Random Walk rules outperform the other two rules for large size of network.

Figure 6 shows the weight distribution in Hebbian learning rule with weight range $\kappa = 5$.

In Random Walk, the weights are well distributed as the Hebbian and Anti-Hebbian rules shown in Figure 7. So, a network with a size greater than 256, Random Walk makes synchronization faster, but for this range Hebbian and Anti-Hebbian take a lot more synchronization steps.

Table 7 provides a comparison of synchronization time for fixed network size and variable learning rules and κ in the proposed DLTPM and the existing CVTPM methods. Table 7 shows a trend towards an increase in synchronization steps as the range of weights κ rises in all three learning rules. For small κ values, Hebbian takes fewer synchronization steps than the other two learning rules, but as the κ value increases then more steps are taken to synchronize than the others. Here, the Anti-Hebbian requires less time than the other two learning rules for mid κ values. Random Walk outperforms for high κ values.

VI. CONCLUSION AND FUTURE SCOPE

For the cryptographic public-key exchange protocol, this article proposes the synchronization of Double Hidden Layer Neural Networks using nature-inspired whale optimization. For the generation of different key lengths using the neural synchronization process, various combinations of $H1$, $H2$, M and κ with variable network sizes are considered. The article analyses the optimization of the weight vector of two DLTPMs using whale optimization algorithms for faster synchronization. DLTPM's security and synchronization time is also examined. It has been shown that geometric attacks have a lower rate of success. It has been found that DLTPM security is higher than the current TPM with the same set of parameters. Finally, in order to verify the experimental findings, a variety of outcomes and evaluations are carried out. A more detailed risk evaluation is expected for future studies to be carried out. In addition, for the optimization of weights for faster neural synchronization purposes, various nature-inspired optimization algorithms will be considered.

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