



# Support Vector Regressive Dragonfly Optimized Shift Invariant Deep Neural Learning Based Handover for Seamless Data Delivery in Heterogeneous Network

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**Abstract** – In a Wireless Sensor Network (WSN), seamless mobility management can change the current mobile node's location point to another network devoid of any link failure during communication. The seamless mobility system is very useful to detect the nearest base station over the wireless network without any distinct interference. In this paper, a novel technique called Support Vector Regressive Dragonfly Optimization based Shift Invariant Deep Neural Learning (SVRDO-SIDNL) is introduced for improving the seamless data transmission with minimum delay. The Shift Invariant Deep Neural Learning comprises of many layers to learn the series of input. For each layer, the different processes are carried out to accomplish the traffic optimized seamless data delivery. The input layer of the deep neural learning receives mobile nodes with coverage region and then is sent to the hidden layer. The mobile nodes' signal strength is analyzed by applying the support vector regression at the hidden layer. Then, the node with weak signal strength is identified and performs the handover. Through oppositional learned multi-objective dragonfly optimization technique, recognition of nearby attachment points with greater bandwidth availability is performed for the handover process. Then, the mobile node connection is altered from the existing attachment point to a new attachment point without losing connectivity. The simulation results reveal that the SVRDO-SIDNL technique offers a greater delivery rate, throughput with lesser packet loss at less delay.

**Index Terms** – Mobility Management System, Shift Invariant Deep Neural Learning, Support Vector Regression, Oppositional Learned Multi-Objective Dragonfly Optimization, Handover.

## 1. INTRODUCTION

Wireless Sensor Network (WSN) facilitates several end devices with stringent latency and elevated bandwidth requirements. Mobility is termed as the process of representing the movement of the mobile user in which the

location, velocity, and speed change over time. Seamless mobility is very useful that permits the user to accomplish their tasks without any concern. Seamless mobility management facilitates the movement of the mobile node irrespective of access technologies, transparent to applications, and higher-layer protocols referred to as TCP.

Handover mechanisms are needed for achieving seamless and lossless handover capabilities in mobility management algorithms to ensure the overall goal of a wireless network. Seamless mobility is planned to generate permanent access to information at any instance, independent of place, network, and device. The seamless mobility system needs to mainly focus on continuous data deliverance with low data deliverance latency. Hence, several learning has tried to appear with suitable clarification to reduce the associated time delay during handover processes. Many handover algorithms were introduced but it has a few limitations.

A two-stage fuzzy-logic based VHO decision scheme [1] pick the appropriate access network for communication. The designed scheme minimizes the delay but it has high packet loss during data communication. A Machine Learning Backed Multimetric Proactive Handover Algorithm (ABRAHAM) was introduced in [2] for mobility and handover management. The designed algorithm reduces the packet delay but data delivery was not improved at the required level. In [21], the game-theoretic approach was presented for handover management. However, this method failed to achieve an efficient data delivery rate.

To overcome the above drawbacks, a novel SVRDO-SIDNL technique is introduced. The novel contribution of the proposed SVRDO-SIDNL technique is listed below,

**RESEARCH ARTICLE**

- To propose a novel SVRDO-SIDNL technique that enhances traffic-aware seamless mobility management by optimizing the handover process. This contribution is achieved through the regression and multi-objective optimization that is embedded in the shift-invariant deep neural network.
- To scrutinize weak and strong signal strength of mobile nodes based on network states in a heterogeneous network by considering support vector regression.
- Secondly, the oppositional learned multi-objective dragonfly optimization technique is applied to optimize the handover process through multiple objective functions and sufficient and provide a dynamic handover process. It reduces delay and data loss during seamless data transmission.
- The simulation analysis explores that the SVRDO-SIDNL technique enhances the handover performance with a greater delivery rate and less delay.

This article is ordered as follows. Section two describes a novel SVRDO-SIDNL technique for the seamless data transmission between the devices with a neat diagram. Section three illustrates the simulation setup and parameter description. Followed by, the comparative analyses of proposed SVRDO-SIDNL and the other two related algorithms are presented. Section-four concludes the proposed SVRDO-SIDNL technique.

## 2. RELATED WORK

An enhanced handover method was developed in [3] with mobility prediction to support mobile devices for seamless connectivity. Though the method increases the throughput, the performance of delay was not minimized.

A Fast Multi-attribute network selection method was introduced in [4] for vertical handover to choose the appropriate network with lesser execution time. But, the designed method failed to consider the available bandwidth measurement for minimizing the traffic during data transmission. A Prediction Handover method was developed in [5] for increasing the higher throughput but, the performance of the delay of packet transfer was not minimized.

An improvised vertical handover decision method was introduced in [6] by incorporating multi-criteria for an accurate and precise handover decision. Though the designed method minimizes the number of handovers failed but the statistical analysis of the delay during the handover was not minimized. An intelligent decision-making system was presented in [7] for efficient handover by applying Fuzzy

Logic. An optimal competitive ratio algorithm was designed in [8] for minimizing redundant handoff during the communication. The algorithm failed to perform the handoff minimization in the sparse or crowded zones.

The Media Independent Handover method was presented in [9] to support the fast heterogeneous handover. Though the mechanism reduces the delay and signaling cost, the distributed seamless mobility management was not considered. A horizontal and vertical handover method was developed in [10] with different measurement factors and minimum latency but higher throughput while distributing the data was not achieved.

A cross-tier handover method was presented in [11] for selecting the base station and minimizing the handover failure rate. But the method failed to perform the handover optimizations in densely deployed heterogeneous networks. A generalized Random Access Channel-less Handover (RACH) method was introduced in [12] for increasing the performance of seamless mobility. But the different QoS metrics were not analyzed. A Coordinated Multi-Point (CoMP) system was developed in [13] to reduce the redundant handovers.

To carry out handover through a fuzzy concept, an Artificial Neural Network (ANN) was designed. However, the model failed to use the optimization technique for finding the optimal network. A genetic algorithm (GA) was employed in [15] to optimize the network attributes' by minimizing redundant handovers.

The designed algorithm performs the traffic optimized handover but the delay was not minimized. To optimize the handover process with lesser time, the Optimized Vertical Handover (OVH) method was designed in [16]. K-partite graph theory was described in [17] to handle the vertical handover and minimize the delay. However, the higher data delivery rate was not achieved.

A Markov Decision Process (MDP) with a genetic algorithm (GA) was presented in [18] to lessen the handover delay. But, the designed GA algorithm failed to consider the multi-objective issues during the handover process. A new selection algorithm was developed in [19] for optimizing access point selection with less computational time. But it failed to consider a more comprehensive model for accurate access point selection.

A new fuzzy-Analytic Hierarchy Process (AHP) was presented in [20] for network selection. But the developed approach failed to perform the seamless handovers. An epidemic diffusion model was implemented in [22] for mobile crowd sensing. But the designed method failed to perform the seamless handovers. In the following Table 1 summarize the major elements of previous methods.



## RESEARCH ARTICLE

Reference Number	Method Name	Merits	Demerits
[1]	Two-Stage fuzzy-Logic based VHO Decision Scheme	Minimizes the transmission delay	High packet loss occurred during data communication
[2]	Machine Learning Backed Multimetric Proactive Handover Algorithm (ABRAHAM)	Reduces the packet delay	Performance of data delivery was not improved
[3]	Enhanced Handover Method	Mobile devices were supported for seamless connectivity. The method increases throughput	The performance of delay was not minimized
[4].	Fast Multi-Attribute Network Selection Method	Chooses the appropriate network with lesser execution time	However, failed to consider the available bandwidth measurement for minimizing the traffic during data transmission.
[5]	Prediction Handover method	Increases the higher throughput	But, the performance of the delay of packet transfer was not minimized
[6]	An Improvised Vertical Handover Decision Method	Incorporates multi-criteria for an accurate and precise handover decision.  The designed method minimizes the number of handovers	But the statistical analysis of the delay during the handover was not minimized
[7]	Intelligent Decision-Making System	Fuzzy Rules were employed to support an energy-efficient approach for saving battery power  Quality of Experience (QoE) was also maintained at satisfactory levels	Decision-making system was not applicable for dynamic scenario
[8]	Optimal Competitive Ratio Algorithm	Minimizes redundant handoff during the communication	The algorithm failed to perform the handoff minimization in the sparse or crowded zones
[9]	Media Independent Handover Method	Supports fast heterogeneous handover	Distributed seamless mobility management was not



## RESEARCH ARTICLE

		Minimizes the delay, signaling cost and	considered
[10]	The Horizontal and Vertical Handover Method	Minimum latency was achieved	However, higher throughput was not achieved while distributing the data
[11]	Cross-Tier Handover Method	Selects appropriate base station to minimize the handover failure rate	But the method failed to perform the handover optimizations in densely deployed heterogeneous networks
[12]	Random Access Channel-Less Handover (RACH) Method	Increases the performance of seamless mobility	But the different QoS metrics were not analyzed
[13]	Coordinated Multi-Point (CoMP) System	Reduce the redundant handovers based on the signal strength	Transmission delay was not reduced
[14]	Artificial Neural Network (ANN)	Performs the handover through the fuzzy concept.	However, the model failed to use the optimization technique for finding the optimal network
[15]	Genetic Algorithm (GA)	Performs the traffic optimized handover  Optimizes the network attributes' by minimizing redundant handovers	But, the delay was not minimized
[16]	Optimized Vertical Handover (OVH) Method	Reduces the handover time and optimizes the handover process	Packet loss rates remain unaddressed
[17]	K-Partite Graph Theory	Handles vertical handover and minimize the delay	However, the higher data delivery rate was not achieved
[18]	Markov Decision Process (MDP) with Genetic Algorithm (GA)	Minimizes the handover delay	But, the deigned GA algorithm failed to consider the multi-objective issues during the handover process

**RESEARCH ARTICLE**

[19]	New Selection Algorithm	Optimized access point selection was performed with less computational time	But it failed to consider a more comprehensive model for accurate access point selection
[20]	Fuzzy-Analytic Hierarchy Process (AHP)	AHP helps for network selection	But the developed approach failed to perform the seamless handovers
[21]	Alpha-Beta Pruning	It acts as a game-theoretic approach for handover management	However, this method failed to achieve efficient data deliver rate
[22]	Epidemic Diffusion Model	The diffusion model helps in mobile crowd sensing	But, failed to perform the seamless handovers

**3. SUPPORT VECTOR REGRESSIVE DRAGONFLY OPTIMIZATION-BASED SHIFT INVARIANT DEEP NEURAL LEARNING (SVRDO-SIDNL)**

A novel SVRDO-SIDNL technique is introduced for enhancing the traffic-aware seamless data allocation in an assorted wireless network. This section starts to design a network model followed by a brief explanation of the proposed SVRDO-SIDNL technique is presented.

**3.1. Network Model of SVRDO-SIDNL**

The network model of the proposed SVRDO-SIDNL technique is described. The heterogeneous wireless network comprises of several mobile nodes  $mn_1, mn_2, mn_3, \dots, mn_n$  deployed over a particular transmission range ' $T_r$ '. The process of the seamless mobility model is shown in Figure 1.

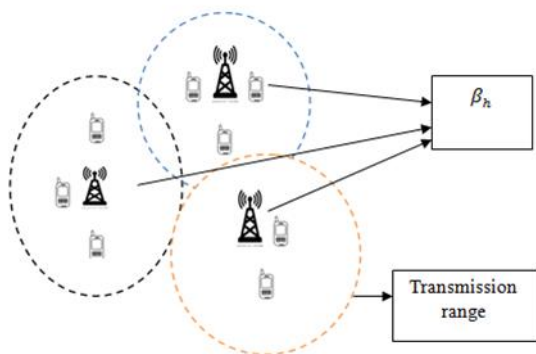


Figure 1 Network Architecture

Figure 1 shows the network architecture of a seamless mobility model. As in Figure 1, the networks surrounded by the coverage range of the device are associated with different network attach points i.e. base station  $ap_1, ap_2, ap_3, \dots, ap_m$ . When the mobile devices shifts away from the current network, the breakdown of a direct link may occur and signal strength may become poor from the current network. In this

case, the devices are handled by the nearby possible access network to support seamless services. Using this network model, the proposed SVRDO-SIDNL technique is designed.

**3.2. Support Vector Regressive Dragonfly Optimization based Shift Invariant Deep Neural Learning**

SVRDO-SIDNL technique applies shift-invariant deep artificial feed-forward neural learning for seamless data delivery by handovering the device from the current network point to other networks. The shift-invariant deep neural learning includes neurons like nodes that are linked to a subsequent layer to form the entire network. The designed architecture comprises several layers. The input from the preceding layer is accepted in each layer.

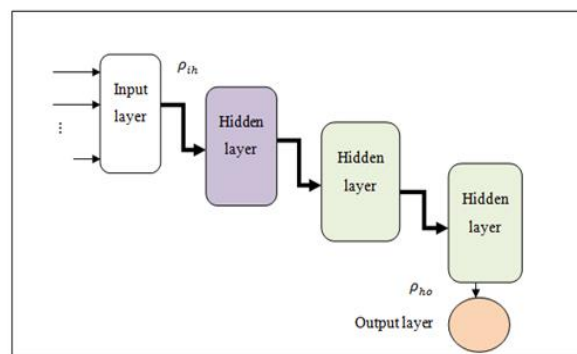


Figure 2 Schematic Structure of Shift-Invariant Deep Artificial Feed-Forward Neural Learning

The schematic structure of deep learning is shown in Figure 2. In Figure 2, the networks inside the coverage range of mobile devices are denoted as input for the first stage i.e. input layer. This layer gets the mobile device at time ' $t$ ' and is denoted as ' $\varphi(t)$ '. The received input is fed into the next consecutive layer i.e. hidden layer. The input and hidden layer are linked with the adjustable weight  $\rho_{ih}$  which is used to strengthen the connection. The regression function is used in the second hidden layer to examine the signal strength of every mobile

**RESEARCH ARTICLE**

device for the handover process. In the third layer, the handover process is said to be performed based on the distance and bandwidth availability. The hidden and output layers are connected with dynamic weights  $\rho_{ho}$ . The shift-invariant process of the deep artificial feed-forward neural learning is given below,

$$F(t) = T [\varphi(t)] \tag{1}$$

From (1),  $F(t)$  is a time-dependent function of deep artificial feed-forward neural learning,  $T$  denotes a transfer function to transform input from one layer to the next layer and  $\varphi(t)$  symbolizes a time-dependent input function.

In the input layer, the signal strength of the mobile nodes  $mn_1, mn_2, mn_3, \dots, mn_n$  from the nearest point are measured as given below,

$$R_{rs} = 10 \log \left[ \frac{p_R}{p_T} \right] \tag{2}$$

In equation (2),  $R_{rs}$  indicates the signal strength of the mobile device,  $p_R$  specifies a measured power and the reference power is represented as  $p_T$ . The signal strength of each device in the current network is measured in terms of decibel (dB).

The measured signal strength of the device is transferred into the next hidden layer for identifying the node status. The signal strength of the node is analyzed by applying the support vector regression function. The regression is a statistical process used for classifying the node according to the status of signal strength.

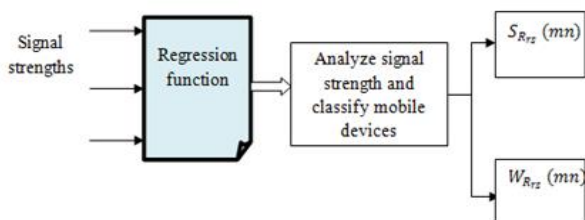


Figure 3 Block Diagram of Support Vector Regression Function

The block diagram of the support vector regression function used to identify the current status of the mobile node as either weak ( $W_{R_{rs}}(mn)$ ) or strong signal strength ( $S_{R_{rs}}(mn)$ ) is shown in Figure 3. The support vector regression makes the use of the separating hyperplane to analyze and classify the signal strength of the mobile node. Followed by, the two marginal hyperplanes are formed on both sides of the hyperplane. Here, the hyperplane act as a threshold between the output classes. A separating hyperplane ( $\beta_h$ ) is defined as follows,

$$\beta_h \rightarrow \vec{w} \cdot (mn) + \vec{b} = 0 \tag{3}$$

From (3),  $\vec{w}$  indicates a normal weight vector to the hyperplane,  $(mn)$  denotes mobile nodes and  $\vec{b}$  denotes a bias. If mobile node signal strength is greater than the threshold, then the mobile nodes are classified by constructing two marginal planes given below,

$$N_1 = \vec{w} \cdot (mn) + \vec{b} > 0 \rightarrow S_{R_{rs}}(mn) \tag{4}$$

$$N_2 = \vec{w} \cdot (mn) + \vec{b} < 0 \rightarrow W_{R_{rs}}(mn) \tag{5}$$

From (4) and (5),  $N_1$  and  $N_2$  signifies the two marginal hyperplanes i.e. above and below the hyperplane. The mobile device which has higher signal strength than the threshold is classified above the hyperplane. The node signal strength is smaller than the threshold is classified below the hyperplane. The classification result of the support vector regression function is shown in below Figure 4.

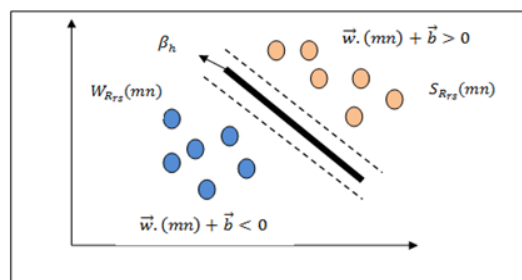


Figure 4 Support Vector Regression based Node Classification

Figure 4 demonstrates a support vector regression to classify the mobile devices into strength or weak based on either side of the hyperplane ( $\beta_h$ ). After the classification, the node with weak signal strength is changed from the present network to the nearest attachment point for continuous data delivery.

In the third layer, the nearest attachment point is identified by applying oppositional learned multi-objective dragonfly optimization. An oppositional learned multi-objective dragonfly optimization is a metaheuristic process to find an optimal one based on swarming behaviors. Initially, the population of dragonflies (i.e.  $ap_1, ap_2, ap_3, \dots, ap_n$ ) is generated in the search space. In other words, the dragonflies are related to the network attachment points. The dragonflies travel back and forward over a region to search for their food source (i.e. objective functions). Here, two objective functions are introduced namely, distance and bandwidth availability. On contrast to the existing optimization technique, the proposed method uses the oppositional learning concept to identify the global best solution in search space. Therefore, the opposite population of the dragonflies against the current populations is generated as follows,

**RESEARCH ARTICLE**

$$Z = \{ap_1, ap_2, ap_3, \dots, ap_n\} \quad (6)$$

From (6),  $Z$  indicates the current population and the opposite population generation is expressed as follows,

$$Z'' = a_i + b_i - [Z] \quad (7)$$

From (7), the opposite population is denoted as  $Z''$  and  $a_i$  and  $b_i$  is the minimum and maximum dimensions value in current population ' $Z$ '. After initialization, the fitness is calculated for each attachment point in the current population as well as the opposite population. The fitness is measured based on two objective functions namely, distance and bandwidth availability. In two dimensional spaces, the mobile node present coordinate is  $(p_1, q_1)$  and the coordinate of the available attachment point is  $(p_2, q_2)$ . The distance among mobile node and attachment point is computed as below,

$$D = \sum_{i=1}^k |p_i - q_j| \quad (8)$$

From (8), ' $D$ ' indicates the Manhattan distance among mobile node and other available attachment points. Based on the distance measure, the neighboring attachment point is identified for the handover process. Then, the bandwidth availability is measured as given below,

$$Bw_{av} = [Bw_T - Bw_U] \quad (9)$$

From (9),  $Bw_{av}$  indicates bandwidth availability,  $Bw_T$  indicates the total bandwidth and  $Bw_U$  indicates the amount of bandwidth utilized. Based on the above-said objective function, the fitness is evaluated as given below,

$$f(\varphi) = \{(\arg \min D) \& (Bw_{av} > T)\} \quad (10)$$

From (10),  $f(\varphi)$  denotes a fitness function,  $\arg \min D$  denotes an argument of minimum distance,  $Bw_{av}$  denotes bandwidth availability and  $T$  denotes a threshold. Among the population, the attachment point with lesser distance and greater bandwidth availability is elected for the handover process. During the data transmission, traffic occurs due to the consumption of the higher bandwidth which causes a higher data loss and maximum latency. To overcome the data loss and delay, maximum bandwidth availability is selected for seamless data transmission from one node to another. After that, the current population and opposite populations of flies are combined and the dragonflies are sorted along with their fitness value. At last, 'n' best flies are chosen from the combination for further processing. Based on the fitness value, the proposed optimization technique performs four tasks namely, separation, alignment, cohesion, and attraction. Based on these tasks, the new optimal solution is determined. These steps are explained as follows. At first, the separation process is carried out for identifying the position of a dragonfly with its neighboring dragonflies as follows,

$$Q = - \sum_{j=1}^k \|P(t) - P_j(t)\| \quad (11)$$

Where,  $Q$  indicates the separation process,  $P(t)$  indicates the position of a dragonfly,  $P_j(t)$  indicates a position of the neighboring solution and ' $k$ ' indicates neighboring dragonflies in search space. Afterward, the alignment process is carried out as given below,

$$A = \frac{1}{k} \sum_{j=1}^k v_j(t) \quad (12)$$

Where,  $A$  specifies alignment step,  $v_j(t)$  signifies the velocity of ' $j^{th}$ ' neighboring dragonfly and ' $k$ ' is the number of neighboring dragonflies. Thirdly, the cohesion process is carried out as follows,

$$S = \left[ \frac{1}{k} \sum_{j=1}^k P_j(t) \right] - P(t) \quad (13)$$

Where ' $S$ ' stands for the cohesion of dragonfly,  $P_j(t)$  is a ' $j^{th}$ ' neighboring dragonfly position,  $P(t)$  is a dragonfly position and ' $k$ ' indicates a neighborhood. Depends on the position of the dragonfly and food source, the attraction to food sources is established.

$$W = |P_s(t) - P(t)| \quad (14)$$

Where,  $W$  is an attraction towards a food source,  $P_s(t)$  is a food source position,  $P(t)$  denotes a current dragonfly position. With the above optimization process, the present dragonfly position is updated,

$$P_{t+1} = P(t) + \nabla P_{t+1} \quad (15)$$

Where,  $P_{t+1}$  indicates an updated position of the dragonfly,  $P(t)$  indicates a position of a current dragonfly,  $\nabla P_{t+1}$  is the step vector which helps to find a moving direction of the dragonfly based on the above-said four processes,

$$\nabla P_{t+1} = [x_1 Q + x_2 A + x_3 S + F b_k] + \vartheta P(t) \quad (16)$$

From (16),  $x_1$  is a separation ( $Q$ ) weight,  $x_2$  denotes alignment weight ( $A$ ),  $x_3$  is a cohesion ( $S$ ) weight,  $F$  indicates a food vector,  $b_k$  is the food source of  $k^{th}$  dragonfly,  $\vartheta$  signifies an inertia weight controls the convergence of optimization,  $P(t)$  symbolizes a dragonfly position at the time ' $t$ '. Finally, the optimal attachment point is chosen for the handover process. The hidden layer output is formalized as below,

$$h(t) = \rho_{ih} i(t) + \rho_{hh} h(t-1) \quad (17)$$

Where  $h(t)$  is the hidden layer output at a time ' $t$ ',  $\rho_{ih}$  indicates a weight among input and hidden,  $\rho_{hh}$  is the hidden layer weight,  $i(t)$  represents the input,  $h(t-1)$  denotes a previous hidden layer output. The deep neural learning output is expressed as below,

$$y(t) = [\rho_{hh} h(t)] \quad (18)$$

**RESEARCH ARTICLE**

From (18),  $y(t)$  signifies the output,  $h(t)$  designates adjustable weights between the hidden and output layer,  $h(t)$  refers to the output of the hidden layer. As a result, the proposed technique continuously performs the data transmission between the device with higher throughput and minimum delay.

**Input:** Number of mobile devices  $mn_1, mn_2, mn_3 \dots mn_n$ ,

**Data Packets**  $dp_1, dp_2, dp_3, \dots dp_n$

**Output:** Enhance seamless data delivery

**Begin**

1. **Number of** mobile devices  $mn_1, mn_2, mn_3 \dots mn_n$  taken as input
2. **For each**  $mn_i$
3. Evaluate signal strength ' $R_{rs}$ '
4. Analyze the signal strength
5. Construct hyperplane ' $\beta_n$ '
6. Find two marginal hyperplane  $N_1, N_2$
7. **If** ( $R_{rs} > \tau$ ) **then**
8. Node is classified as  $S_{R_{rs}}(mn)$
9. **else**
10. Node is classified as  $W_{R_{rs}}(mn)$
11. **End if**
12. **For each**  $W_{R_{rs}}(mn)$
13. **Find nearest attachment point** ' $ap$ '
14. Initialize the current and opposite population ' $Z$ ' and  $Z''$
15. **For each** ' $ap$ ' in  $Z$ ' and  $Z''$
16. Calculate the fitness  $f(\varphi)$
17. Combine the populations of  $Z$  and  $Z''$
18. Sort ' $ap$ ' based on fitness  $f(\varphi)$
19. Select the current best ' $n$ '
20. Measure  $Q, A, S, W$
21. **End for**
22. **If** ( $f(\varphi) > f(\varphi)_{nm}$ ) **then**
23. Update the position of dragonfly ' $P_{t+1}$ '
24. **end if**
25. **If** (Iter < max ) **then**
26. Obtain global best ' $ap$ '

27. **End if**

28. **End for**

29. Handover ' $mn$ ' into nearby optimal attachment point ' $ap$ '

**End**

Algorithm 1: Support Vector Regressive Dragonfly Optimization-based Shift Invariant Deep Neural Learning

Algorithm 1 given above describes the process of support vector regressive dragonfly optimization-based shift-invariant deep neural learning. Input mobile nodes are considered as input for identifying the strong and weak signal strength based on the support vector regression. The node signal strength is better than the threshold ( $\tau$ ) is said to strong signal strength. Otherwise, the node is classified as weak signal strength.

After the detection of weak signal strength of the mobile node, the nearby attachment point is discovered depends on multi-objective oppositional learned dragonfly optimization. For each attachment point, the fitness is computed based on distance measure and bandwidth availability. Based on the fitness evaluation, the optimal attachment point is identified and selected for the handover process. Then, the weak signal strength of the mobile node is switched to the best network attachment point to enhance the traffic optimized seamless data delivery with minimal loss.

4. RESULTS AND DISCUSSIONS

The proposed SVRDO-SIDNL technique and the conventional [1], [2], and [21] are implemented in the NS2 network simulator. IP Network Traffic Flows Labeled with 75 Apps dataset [<https://www.kaggle.com/jsrojas/ip-network-traffic-flows-labeled-with-87-apps>] is used to handle the simulation. The data is gathered during morning and afternoon over six days (April 26, 27, 28, and May 9, 11, and 15) of 2017. The dataset comprises of 87 features and multiple instances were gathered and currently accumulated in a CSV.

Each instance includes IP information flow executed by network device i.e., source and destination IP addresses, ports, inter-arrival time, and layer 7 protocol. Many features are numeric type but it includes few nominal types and date types owing to Timestamp. Some of the attributes are Flow ID, source IP, Source port, destination IP, destination port, timestamp, flow duration, total forward packets, total backward packets, forward packets length, backward packets length, and so on.

For performing the simulation, 500 mobile nodes are positioned over the square area of  $A^2(1200 m * 1200 m)$ . Random Waypoint is employed as a mobility model. 25 to



**RESEARCH ARTICLE**

250 data packets are considered to carry out seamless data delivery. The simulation time is set as 100 sec. To perform seamless data transmission, the DSR protocol is applied. The node's speed is taken from 0-20m/sec.

4.1. Evaluation of Metrics

The various performance metrics are used for conducting the simulation which is described as follows,

4.1.1. Data Delivery Rate

It is measured as a ratio of data packets that are effectively delivered from the source.  $R_D$  is formalized as below,

$$R_D = \left[ \frac{CR(dp_n)}{dp_n} \right] * 100 \quad (19)$$

From (19),  $R_D$  indicates data delivery rate,  $dp_n$  is the number of data packets sent from source and  $CR(dp_n)$  indicates correctly received packets.  $R_D$  is calculated in percentage (%).

4.1.2. Packet Loss Rate

It is the number of data packets lost during the transmission and measured as given below,

$$R_{PL} = \left[ \frac{L(dp_n)}{dp_n} \right] * 100 \quad (20)$$

Where ' $dp_n$ ' indicates the number of a packet sent and  $L(dp_n)$  denotes data packet lost. Therefore, the packet loss rate during the seamless transmission is measured in percentage (%).

4.1.3. Data Transmission Delay

Delay is defined as the amount of time consumed to receive the data packets. The overall data transmission delay is calculated as given below,

$$D_T = [t(dp_R) - t(dp_T)] \quad (21)$$

Where ' $D_T$ ' denotes data transmission delay, ' $t(dp_R)$ ' denote data packets receiving time, and ' $t(dp_T)$ ' represents time for transmitting the data packets. Data transmission delay is calculated in milliseconds (ms).

4.1.4. Throughput

It is the final metric that is data packets size delivered in destination within a particular time. The throughput is mathematically calculated as given below,

$$Throughput = \left[ \frac{S_{dp}(bits)}{t(sec)} \right] \quad (22)$$

From (22), ' $S_{dp}$ ' indicates the size of data packets delivered in terms of bits at the destination, and  $t(sec)$  denotes a particular time in second (sec).

4.2. Simulation Results and Discussion

In this section, the proposed SVRDO-SIDNL technique and existing [1], [2], and [21] are discussed with four metrics.

4.2.1. Scenario 1: Data Delivery Rate Versus the Number of Data Packets

Table 2 shows the average data delivery rate versus a number of data packets in the range of 25 to 250.

Data packets (numbers)	Data delivery rate (%)			
	Game-theoretic approach	Two-stage fuzzy-logic-based VHO decision scheme	ABRAHAM	SVRDO-SIDNL
25	72	76	84	96
50	80	82	88	96
75	82	84	89	97
100	81	83	87	96
125	80	82	89	97
150	76	79	86	94
175	82	84	88	96
200	84	86	89	97
225	80	83	87	95
250	85	88	89	97

Table 2 Data Delivery Rate Comparison of Three Methods

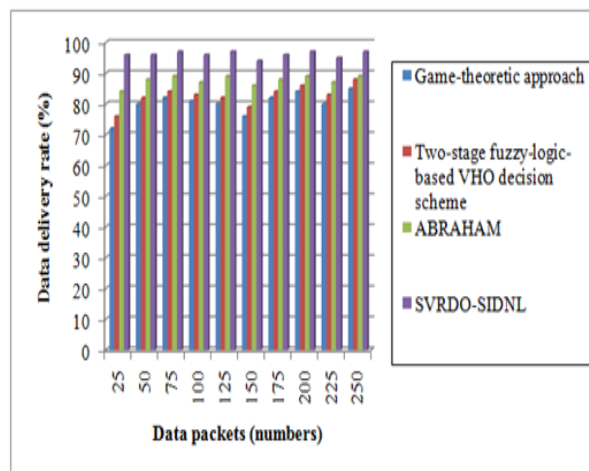


Figure 5 Simulation Results of Data Delivery Rate

From the simulation results, it is inferred that the data delivery rate was found to be higher using the SVRDO-SIDNL technique than the other three related works. This is confirmed by the statistical analysis. Let us consider 25 data packets being sent from the source, 24 data packets are effectively delivered at the destination, and then the data delivery rate observed is 96%. Similarly, 19 data packets and 21 data packets and 18 are successfully received at the destination and the observed delivery rates are 76% and 84%, and 72% respectively. Likewise, remaining runs are

**RESEARCH ARTICLE**

performed with different counts of data packets. The average of ten results proves that data delivery is found to be higher by 16% as compared to [1], 10% as compared to [2], and 20% as compared to [21]. The various results of the data delivery rate using three methods are illustrated as exposed in Figure 5.

The impact of the data delivery rate is portrayed in Figure 5 using three methods. As in the figure, the proposed SVRDO-SIDNL technique gives a better delivery rate when compared to [1], [2], and [21]. This is owing to the application of SVRDO-SIDNL. The proposed learning technique efficiently performs the handover process by switching the mobile nodes into the nearby base station. The oppositional learned dragonfly optimization finds the global optimum available base station with the help of distance and bandwidth availability. After finding the nearest base station, the mobile node is handover to the optimal base station. This ensures continuous data delivery from the source point to the destination.

**4.2.2. Scenario 2: Packet Loss Rate Versus the Number of Data Packets**

In this scenario, the packet loss rate of three different methods is discussed with a number of data packets in the range from 25 to 250.

Data packets (numbers)	Packet loss rate (%)			
	Game-theoretic approach	Two-stage fuzzy-logic-based VHO decision scheme	ABRAHAM	SVRDO-SIDNL
25	28	24	16	4
50	20	18	12	4
75	18	16	11	3
100	19	17	13	4
125	20	18	11	3
150	24	21	14	6
175	18	16	12	4
200	16	14	11	3
225	20	17	13	5
250	15	12	11	3

Table 3 Packet Loss Rate Comparison Using Three Methods

Table 3 reports the simulation results of the packet loss rate with three different methods. The observed results indicate that the proposed SVRDO-SIDNL technique achieves less error rate than the other two methods. By considering 25 data packets, 1 data packet is lost using the SVRDO-SIDNL technique and the loss rate is 4%. By applying the other three

methods [1], [2] and [21], 6, 4, and 7 data packets are lost and their percentages are 24%, 16%, and 28% respectively. Similarly, the various loss rates are observed for the different counts of data packets. Ten results are observed for all the methods. The average packet loss rate of the SVRDO-SIDNL technique is minimized by 77% when compared to [1], 68% when compared to [2], and 80% when compared to [21].

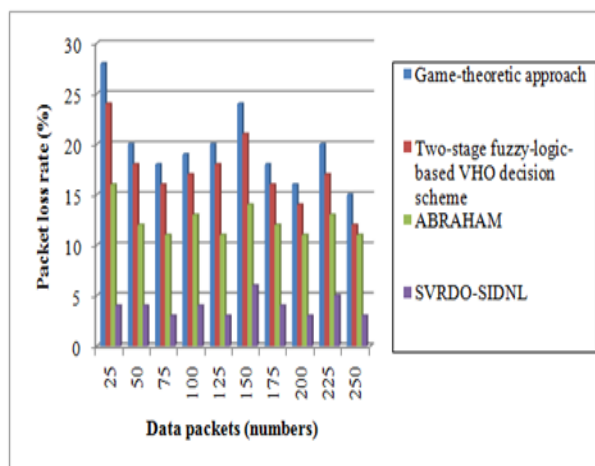


Figure 6 Simulation Results of Packet Loss Rate

The results of the packet loss rate using three methods are depicted in Figure 6 with the number of data packets. From Figure 6, the packet loss rate of the SVRDO-SIDNL technique is identified to be less. The reason is that the application of oppositional learned multi-objective dragonfly optimization. The proposed optimization considers the maximum bandwidth availability for continuous data transmission resulting in it minimizes the data loss.

**4.2.3. Scenario 3: Data Transmission Delay Versus the Number of Data Packets**

The delay is measured using three methods with the number of data packets.

Data packets (numbers)	Data transmission delay (ms)			
	Game-theoretic approach	Two-stage fuzzy-logic-based VHO decision scheme	ABRAHAM	SVRDO-SIDNL
25	17	15	12	10
50	21	19	16	14
75	26	24	20	17
100	30	27	23	20

**RESEARCH ARTICLE**

125	32	28	25	22
150	34	30	26	24
175	35	33	30	27
200	38	36	32	30
225	41	39	36	32
250	43	41	38	33

Table 4 Comparison of Data Transmission Delay Using Three Methods

Table 4 provides the simulation outcomes of data transmission delay. As in the table, the data transmission delay is increased while raising the number of data packets. But SVRDO-SIDNL technique increases the seamless data delivery with minimum delay. This is proved by the numerical simulation results derived from the mathematical expressions. The simulation analysis is performed with 25 data packets and it calculates the delay. The transmission delay is 10 ms using the SVRDO-SIDNL technique and the delays of the other three methods [1], [2], and [21] are observed as 15ms, 12ms, and 17ms respectively. The various simulation results are observed and are plotted in the Figure 7.

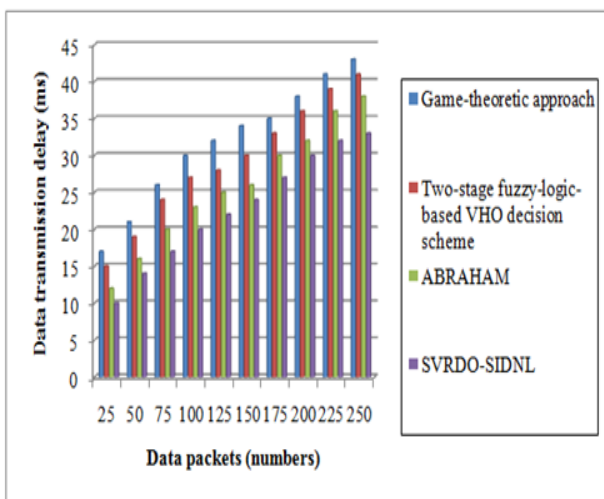


Figure 7 Simulation Results of Data Transmission Delay

The data transmission delay is illustrated in Figure 7. The delay of the SVRDO-SIDNL technique is minimized, by applying the support vector regression, then mobile node signal strength is determined while transmitting the data packets. The node which has weak signal strength is identified and it is switched to the best nearest point. Besides, the handover process of the SVRDO-SIDNL technique reduces data transmission delay from source to destination. The nearby attachment point is identified through multi-objective optimization. As a result, the proposed SVRDO-SIDNL technique outperforms well than conventional methods.

4.2.4. Scenario 4: Throughput versus the size of the data packets

The final metric of seamless mobility management is the throughput which helps to measure the data packets size obtained in the destination. Throughput is calculated depending on the data packets sizes being sent from the source. Results of the throughput versus sizes of the data packets are tabulated in Table 5.

Size of packets (KB)	Throughput (b/sec)			
	Game-theoretic approach	Two-stage fuzzy-logic-based VHO decision scheme	ABRAHAM	SVRDO-SIDNL
10	155	152	165	186
20	250	245	280	355
30	370	365	421	515
40	451	456	538	612
50	565	563	640	765
60	675	670	742	812
70	735	730	822	960
80	815	810	940	1025
90	970	968	1035	1127
100	1140	1138	1240	1340

Table 5 Comparison of Throughput Using Three Methods

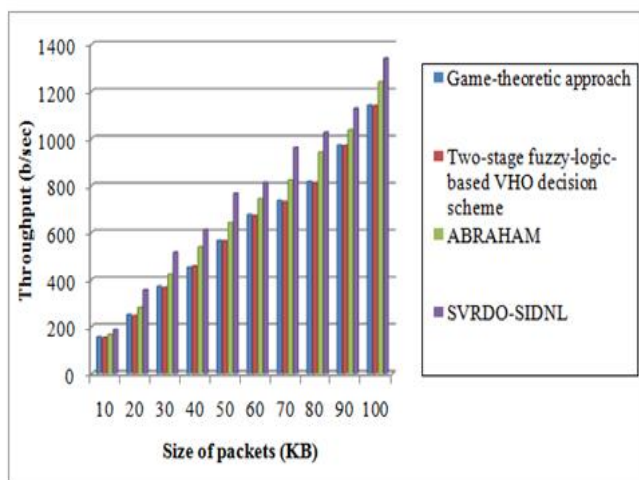


Figure 8 Simulation Results of Throughput

Table 5 and Figure 8 reveals the simulation outcomes of throughput against the data packet size taken from 10KB to

**RESEARCH ARTICLE**

100 KB being transmitted from the source mobile node. As illustrated in figure 5, the throughput of the SVRDO-SIDNL technique is relatively higher than the existing methods [1], [2], and [21]. This is due to the proposed technique that accurately performs seamless data transmission through the handover process. The optimization process discovers the new access network for providing seamless services. The maximum available bandwidth increases the data communication increasing throughput.

Let us consider 10KB of the data being sent from the source mobile node, the SVRDO-SIDNL technique receives 186bits of data per one second. Similarly, the amount of data packet received is 152 bits, 165 bits, and 155 bits by applying the other three existing techniques [1], [2], and [21] respectively. The remaining nine results are obtained for all methods. The average comparison results confirm that the proposed SVRDO-SIDNL technique achieves higher throughput by 29%, 15%, and 28% in seamless data transmission when compared to the conventional handover methods.

**5. CONCLUSION**

This paper has proposed a novel SVRDO-SIDNL technique to support high-speed heterogeneous handover through deep learning-based regression and optimization techniques. Maintenance of handover is significant for enclosing proper seamless mobility management. To offer the demands of handover methods, we first proposed a support vector regression to analyze the signaling strength of the mobile node that is capable of identifying the mobile node with weak signal strength. The evaluation of the handover algorithms is performed to switch the weak signal strength mobile node in the current access point to an available network by applying multi-objective dragonfly optimization. The proposed optimization technique is used for determining the best candidate network during the handover process to preserve traffic-aware network connection. The main aim is to provide efficient seamless handover with better bandwidth allocation. The simulation is conducted for analyzing the performance of the SVRDO-SIDNL technique and for the two existing handover algorithms with different metrics. Comparisons were carried out with the proposed SVRDO-SIDNL technique versus conventional Handover schemes. The observed explores that the SVRDO-SIDNL technique is more efficient with higher data transmission rate, throughput, and less delay as well as packet loss.

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**RESEARCH ARTICLE**

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