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# A Novel Adaptive Extreme Learning Machine for Traffic Prediction and Multipath Routing Framework in Software Defined Networks With Hybrid Optimization Approach for Smart Hotel Applications

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## ABSTRACT

**Problem Statement:** The revolutionary growth of software-defined networking (SDN) has provided a flexible framework to design and improve network management. In a wide range of networks, traffic congestion remains a major challenge. When handling massive amounts of data, it can easily lead to scalability issues due to the rapid network growth, which negatively impacts network performance. Therefore, traffic prediction becomes a quite challenging task. In addition, SDN has proven successful in various applications within wireless communication systems. For enabling better data transmission, efficient routing is essential. During the routing process, energy consumption and link breakage often increase, which limits overall network performance.

**Methodology:** A new traffic prediction and multipath routing model in SDN is developed based on machine learning techniques. The machine learning approach is utilized to develop an effective traffic prediction and multipath routing framework in the SDN system, considering flow rule space and Quality-of-Service constraints. Initially, the traffic present in the network is predicted using an Adaptive Extreme Learning Machine (A-ELM), whose parameters are tuned using the proposed Hybrid Position of Sheep Flock and Tunicate Swarm (HP-SFTS) algorithm. Here, routing performance is improved through the HP-SFTS, which effectively minimizes both the volume of routed traffic and the cost of communication path routing. In performance validation, the developed model accurately traces network traffic and also demonstrates resilience to noise in the training data.

**Results:** From the comparative analysis, the developed HP-SFTS-A-ELM model achieved scores of 37.25, 10.979, and 1387.6 in terms of root mean square error, mean absolute error, and mean squared error, respectively.

**Implications of the Study:** Considering the use of SDN in traffic prediction and multipath routing, this approach is primarily applicable in areas such as data center management, traffic engineering, and network slicing. SDN helps to enhance network performance by transmitting data through less congested routes, and it offers a better computational efficiency rate compared to classical techniques in different experimental analyses.

## 1 | Introduction

In the current and future scenario, short-range detection radar (SDR) is emerging as a key technique for managing wireless communication systems (WCS) effectively. As of today, SDR is primarily recommended for different purposes, yet the devices still require similar functionalities [1]. Reprogrammability and reconfigurability are the two major aspects of WCS. Such technical features help deliver strong performance in high-tech systems like field-programmable gate arrays (FPGAs), which have also become an essential component in SDR [2]. Meanwhile, over the network environment, network traffic has gradually increased and is now applied in several applications like social media, internet applications, internet of things (IoT), cloud services, and smartphones [3]. Conversely, the demand for traffic solutions and routing has increased to accommodate real-time needs, which results in huge traffic congestion. Hence, the legacy network architecture is getting affected as it becomes coupled with both the control and data planes [4]. Moreover, "software-defined networking (SDN)" is an emerging architecture that possesses many traits like programmability, dynamic network management, and performance optimization. Similarly, the model supports a decoupled architecture, where data forwarding and network control are separated by shifting the control to the control plane [5]. Therefore, SDN helps build a more effective programmable model and routing process with significant improvements in network architecture and granular control over traffic resources.

In the view of both industry and academia over the past few years, it has promoted the Internet as a programmable, more open, and manageable infrastructure [6]. Moreover, the control function maintains the network status and handles routing issues like flow rules or entities in the data plane. Depending on the network instructions, the data packets are forwarded and this enables flexible network management, efficient service deployment, and low running costs [7]. However, it faces some vulnerabilities and bottlenecks in the network structure [8]. In addition, the data plane still lacks sufficient accountability measures to satisfy requirements of integrity and efficiency. Due to the presence of a control and data plane, SDN can permit malicious activities [9]. Attackers are able to carry out malicious actions like forging counter values, eavesdropping on data packets, and tampering with network rules, all of which affect the system's robustness [10]. By altering or removing flow rules in the network, attackers can intrude, misuse the data packets, and also affect the firewall.

Owing to several hindrances, security remains a major challenge in SDN. In addition, intruders can degrade the routing efficiency [11]. Experts have developed various effective methods to address routing issues in the network, where they estimate the security of network devices like switches, probes, and so on [12]. Thus, it ensures the security level among the channels used for routing. In recent days, deep learning and machine learning models [13] have been deployed to support this objective and establish a connection between networking and machine learning [14]. Control shifts are used to enable an effective computing paradigm, such as Graphics Processing Units (GPUs), which can be employed with the essential traits of an intelligent network [15]. Additionally, data packets are forwarded with a global view perception, and the Central Controller (CC) [16] enhances the real-time application of machine learning models [17].

### 1.1 | Motivation of SDN in Hotel Applications

With the continuous development of information technology, many research experts have developed models related to hotel applications. In hotel applications, SDN provides certain services such as Quality of Service (QoS) and other security-related mechanisms [18]. It processes a wide variety of data, which can cause the network to become congested with heavy traffic. Traffic issues also affect the extraction of significant information for forwarding and control processes [19]. Thus, this results in reduced scalability and reliability. Therefore, hotel applications integrated with SDN can actively monitor network traffic and diagnose threats effectively. When longer paths are used, link failures may occur in SDN. This affects the routing process in the network and can also disrupt communication, especially in hotel applications [20]. In dynamic network topologies, network congestion reduces the overall network lifetime. The use of existing routing algorithms is not efficient in SDN, which limits convergence and hinders the evolution of network lifetime [21]. Furthermore, existing algorithms are not capable of handling large volumes of data, which degrades decision-making performance in traffic prediction. To address these limitations in existing methods, an innovative model has been developed for traffic prediction and multipath routing in SDN.

*Requirements of hotel applications*: The requirements of a hotel application may vary depending on local regulations, aiming to provide a comprehensive overview of the hotel project, demonstrating its viability and potential impact on the community. In an SDN network, the requirements of a hotel application include comprehensive wireless coverage, improved network stability, and bandwidth allocation for different user types (guests and staff). Dynamic adjustments are made based on guest fluctuations and usage patterns, leveraging the flexibility offered by SDN technology.

By considering all the facts, a new intelligent model is proposed using a hybrid heuristic algorithm combined with recent techniques.

The prime offerings of the proposed work are highlighted as follows:

- To design novel traffic prediction and multipath routing mechanisms to avoid congestion and failures in SDN, this are also useful for applications such as smart hotel management.
- To develop A-ELM for predicting network traffic, this is accomplished by gathering data from standard sources. In addition, for further improvement, hyperparameters are optimally selected using the HP-SFTS algorithm.
- To derive multipath routing by selecting the optimal path with the help of HP-SFTS, this is then used to formulate the objective function with multiple constraints.

- To design a hybrid heuristic algorithm named HP-SFTS, where the conventional Sheep Flock Optimization Algorithm (SFOA) is enhanced with the Tunicate Swarm Algorithm (TSA) to determine the optimal parameters in A-ELM and select efficient paths to improve network performance.

The introduction part is followed by the literature review of prediction and routing works in SDN is given in Section 2. Section 3 portrays the system model and dataset description. The novel algorithm and intelligent prediction model is illustrated in Section 4. Section 5 elucidates the multipath routing process and its objective function. The simulation results are discussed in Section 6. Finally, the paper is concluded in Part VII.

## 2 | Literature Review

### 2.1 | Existing Works

In 2015, Vitas et al. [22] recommended a new model using wireless technologies such as Z-Wave and ZigBee, which enhanced home automation systems to be more secure and energy efficient. Normally, SDR is used in future generations of mobile or wireless communication systems. The SDR system was implemented to introduce local radio networks, which were integrated into smart home infrastructure. Finally, the performance was examined and measured through relevant evaluation metrics. On the contrary, the proposed system achieved better efficiency than existing methods.

In 2021, Rajkumar et al. [23] presented the Mixed-Integer and Reinforcement Learned Network Optimization (MI-RLNO) model for monitoring the SDR network. It was designed with two stages. During network operation, the proposed work formulated mathematical models to improve performance. Simulation analysis was carried out using diverse measures, which enhanced the system's robustness.

In 2017, Alvizu et al. [24] developed a novel dynamic optical routing system for SDR-based networks. The system addressed the issue of offline mixed-integer linear programming by considering both routing and wavelength. Lastly, the model's efficacy was evaluated, and the results demonstrated the system's efficiency compared to other baseline approaches.

In 2021, Khattar et al. [25] explored a Machine Learning-Based Multipath Routing (MLMR) approach for building an effective SDR, which solved QoS and space constraints. The proposed system improved network status and routing configurations that existed in the network for generating a mapping function. After the function was learned, it was applied using the input attributes of routing and network status to solve the routing problem. Therefore, the performance was validated and produced promising results. However, the MLMR model suffered from lower computational efficiency.

In 2020, Rischke et al. [26] enhanced a reinforcement learning model for SDN. The improved method generated results for estimating optimal routing paths during network flow. Due to direct network flow handling, the QR-SDN model was designed to enable better and multiple routing processes between source and destination pairs. In the proposed model, data packets traveled through routing paths, which were established over various routes. Finally, the extensive results proved that the system improved routing performance compared with conventional methods.

In 2023, Dwaraka et al. [27] proposed an efficient path selection strategy in SDN using a Balancing Module (BM) along with Spider Monkey Optimization (SMO) and Crow Search Algorithm (CSA). This model enhanced system efficiency. The BM was also used to overcome the local optima problem and accelerate convergence speed. Consequently, deep reinforcement learning was also applied to schedule resources in SDN. A reward function was used to improve system robustness. Compared with other classical methods, the proposed BM-SMO-CSA achieved lower energy consumption and increased overall efficiency.

In 2022, Yan et al. [28] implemented a Graph Neural Network (GNN)-based model to support multipath routing and improve performance. It also introduced a flowlet-aided solution to balance packet reordering and transmission granularity, which significantly improved data delivery. Initially, an adaptive flow method was used to allow multipath transmission, even under dynamic conditions. Consequently, GNN helped in managing the data while forwarding and splitting in multipath selection. The proposed model was implemented and showed impressive results in terms of delay, throughput, overhead, and completion time. As a result, scalability and reliability were improved, enabling more effective routing.

In 2021, Ren et al. [29] designed a Multipath Resilient Routing (MRR) model for securing SDN architecture. The method refined routing rules and content for consistency with routing strategies. In the enhanced MRR model, a feedback scheme was introduced to support encryption-based authentication. This method was able to prevent malicious intrusions. Therefore, the model achieved high accuracy in transmission flow and system reliability. It also ensured better efficacy in terms of bandwidth, jitter, and delay during routing path selection in the network.

### 2.2 | Problem Statement

SDN effectively enhances both the flexibility and programmability in the communication network. However, malicious attacks create more vulnerability in the system and are subject to tampering with data and network rules. The features and challenges of existing multipath routing approaches for SDN using different techniques are displayed in Table 1. ZigBee and Z-Wave [22] support a large number of nodes and can handle thousands of devices in a single network. However, they have a low transmission rate and a minimal bit rate. MI-RLNO [23] effectively tunes convergence time and latency during analysis and also has a better throughput rate. Still, it requires more data for analysis and involves high computational complexity. Online routing [24] effectively resolves offline issues in optimal routing and also offers optimized predicted traffic patterns for analysis. However, it does not resolve delay and overhead issues in dynamic routing. MLMR [25] offers better computational efficiency in terms of accuracy and is also more flexible. However,

**TABLE 1** | Features and challenges of existing multipath routing models for software defined networks.

| Author [citation] | Methodology | Features | Challenges |
|---|---|---|---|
| Vitas et al. [22] | Zigbee and Z-Wave | • It has more numbers of nodes and also it can support thousands of nodes in a single network. | • It has poor transmission rate and has minimal bit data rate. |
| Rajkumar et al. [23] | MI-RLON | • It effectively tunes the convergence time and the latency in the analysis.<br>• It has better throughput rate. | • It needs more data for analysis and also includes more computation process. |
| Alvizu et al. [24] | On-line routing | • It effectively resolves the off-line issues presented in optimal routing.<br>• It offered optimized predicted traffic patterns for the analysis. | • It didn't resolve the delay and overhead issues in dynamic routing. |
| Khattar et al. [25] | MLMR | • It has better computational efficacy rate in terms of accuracy.<br>• They are more flexible. | • It needs more space to store the data and also requires more knowledge. |
| Rischke et al. [26] | Reinforcement learning | • It has minimal latency rate than the single-path routing technique in high loads. | • It didn't resolve the slow convergence issues. |
| Dwaraka et al. [27] | SMO and CSA | • It effectively enhances the efficacy rate in local optima.<br>• It improves the convergence rate. | • It needs to resolve the energy consumption issue to attain accurate outcome. |
| Yan et al. [28] | GNN | • It commonly enhances the transmission efficacy rate and also achieved multipath transmission.<br>• It has better convergence and throughput rate. | • It faces more space and time complexity issues.<br>• It didn't works effectively in noisy background. |
| Ren et al. [29] | MMR | • It effectively repairs and locates the malicious switch quickly and more accurately.<br>• It utilized abnormal information to improve the decision accuracy. | • It needs to enhance the security rate in transmission flow and also needs to improve the QoS.<br>• It didn't resolve the overhead issue in bandwidth. |

it requires more memory for data storage and demands greater domain knowledge. Reinforcement learning [26] achieves lower latency compared to single-path routing under high loads, but it fails to resolve slow convergence problems. SMO and CSA [27] effectively enhance performance in local optima situations and improve convergence rate. However, they still need to address energy consumption issues to achieve more accurate outcomes. GNN [28] generally improves transmission efficiency and supports multipath transmission, achieving better convergence and throughput. Yet, it suffers from high space and time complexity and performs poorly in noisy environments. MRR [29] effectively detects and repairs malicious switches accurately and uses abnormal information to improve decision accuracy. However, it still needs to improve the security of data transmission, enhance QoS, and address bandwidth overhead issues.

## 3 | Novel Traffic Prediction and Multipath Routing Mechanism in SDN for Smart Hotel Application: Hybrid Heuristic Enhancement

### 3.1 | Software Defined Network

SDN has become one of the most fascinating network architectures to deploy and use in various real-time applications. It also offers flexibility, scalability, and sufficient capability for transmitting data packets efficiently from one place to another. Since it is more innovative and appealing in design compared to other networks. The SDN model also includes controllers, which help to achieve controllability and programmability. Earlier traditional networks faced configuration and troubleshooting issues during transmission. Thus, such networks required high technical skills to resolve problems, which made the system less cost-effective. To overcome these challenges, the SDN model was developed and implemented. Traditionally, SDN differentiates the forwarding and routing processes by assigning roles to specific network devices like switches, routers, and access points. This comes under the data plane of the network. Furthermore, the complexity in SDN is reduced by utilizing the control plane, which operates based on information such as network topology, routing traffic, and other parameters.

Some key points of using SDN in recent developments are elaborated as follows:

- It is highly effective in handling network complexities, as SDN has the potential to control and manage access to networking devices.
- The SDN controller is used not only for monitoring or measuring service parameters but also for making better decisions in resource allocation and routing [30].
- Since SDN is structured with two separate planes, it improves system efficiency by centralizing control over all devices.

- It is a cost-saving model that enables efficient network management, faster scalability, and simplified operations.
- It is mainly used to automate the functioning of devices like switches and routers, which enhances performance and benefits the end user.

### 3.2 | Problem Formulation

Due to the rapid development of technologies, SDN plays a pivotal role in modern networking. Although it contains many advantages, it still faces two major problems: traffic and routing within the network.

Traffic problems in SDN are listed below:

- When SDN handles a massive amount of data through the controller, it may lead to congestion. This congestion is nothing but network traffic that reduces performance.
- The main issue occurs when the network is unable to deliver the correct data to the receiver due to traffic congestion. This congestion also lowers the quality of the network's links or communication channels.
- Heavy network traffic creates opportunities for various attacks, as it can weaken the firewall and overall security.

Routing problems in SDN are pointed out as follows:

- Efficient routing is important, but addressing traffic-related issues is equally critical. As the model includes multiple devices, several transmission paths are created.
- Each device has different resources available for routing, but without proper resource allocation, the routing process suffers, leading to poor network performance.
- When switching or changing paths, routing may be interrupted due to link failures or security threats.
- Poor routing can cause issues such as high end-to-end delay, slow file sharing, increased traffic, and reduced QoS parameters.

In conclusion, both traffic and routing problems must be addressed in current and future technological advancements. To reduce these issues, predicting traffic is necessary to prevent congestion. Similarly, multipath routing is recommended, as it can select the shortest or most optimal path, thereby improving the system's efficiency.

### 3.3 | Description of Proposed Traffic Prediction and Multipath Routing

Due to the emergence of SDN, it is now used in various applications alongside network devices. The network policies are also involved in maintaining consistent performance in terms of throughput, latency, congestion, and other parameters. Nevertheless, a large number of data flows and increased network size is susceptible to causing traffic congestion over the network. This leads to network complexity, which degrades system efficiency. Therefore, traffic prediction becomes essential, as it helps to improve network reliability and also supports better routing decisions. In addition to this, routing is another major challenge in SDN. Because of existing traffic in the network, routing strategies often fail to deliver optimal performance. Several routing algorithms have been implemented, yet they possess drawbacks that prevent effective results. In the routing process, finding the shortest path is often difficult. Without knowing the proper attributes of each node, routing efficiency is negatively affected. Compared to other applications, SDN is especially useful in hotel management systems. Since hotel networks are extensive in nature, both traffic forecasting and routing are essential. In hotel applications, SDN interacts with users such as guests ordering food or booking rooms, where the network manages all internal resources. Also, in recent days, traffic prediction has been performed using machine learning or deep learning models. Classifiers like "Support Vector Machine (SVM), Naïve Bayes (NB), Deep Neural Network (DNN)," etc., are employed. Though these models have been used, they still suffer from issues like parameter sensitivity, structural limitations, or high time complexity, which can mislead the process. To overcome these challenges, a hybrid heuristic algorithm is developed for both traffic prediction and multipath routing in SDN. The architecture of the proposed SDN model is illustrated in Figure 1.

The proposed framework consists of two main components: (i) traffic prediction and (ii) multipath routing. In the first scenario, traffic-related data is collected from the data source. Then, the collected data is used as input for the novel A-ELM model to forecast the level of network traffic. In the proposed A-ELM model, the parameters are optimally tuned using the HP-SFTS algorithm to enhance system efficiency. Subsequently, SDN employs multipath routing, where the shortest path is determined using the proposed HP-SFTS approach. Subsequently, SDN utilizes multipath routing, and the shortest path is identified by using the proposed HP-SFTS approach. Finally, the performance of the model is evaluated and compared against other classical methods. "The results demonstrate that the recommended approach outperforms existing methods in terms of prediction and routing, leading to improved network efficiency."

## 4 | Description of Hybrid Heuristic Algorithm and Adaptive Extreme Learning Machine for Traffic Prediction in SDN

### 4.1 | Hybrid Heuristic Algorithm: HP-SFTS

The novel optimization algorithm is developed to provide a promising and optimal solution for enhancing system performance, referred to as HP-SFTS. The proposed optimization algorithm is developed by combining two conventional algorithms, namely SFOA and TSA. The advantages of SFOA include a better trade-off between exploitation and exploration phases, utilization of fewer parameters, and improved efficiency. The TSA helps to avoid the local optima problem and maintain the transition balance between exploration and exploitation. Nevertheless, the limitations of these two algorithms include premature convergence, insufficient information for the foraging process, difficulty in deriving multi-objective functions, and so on.

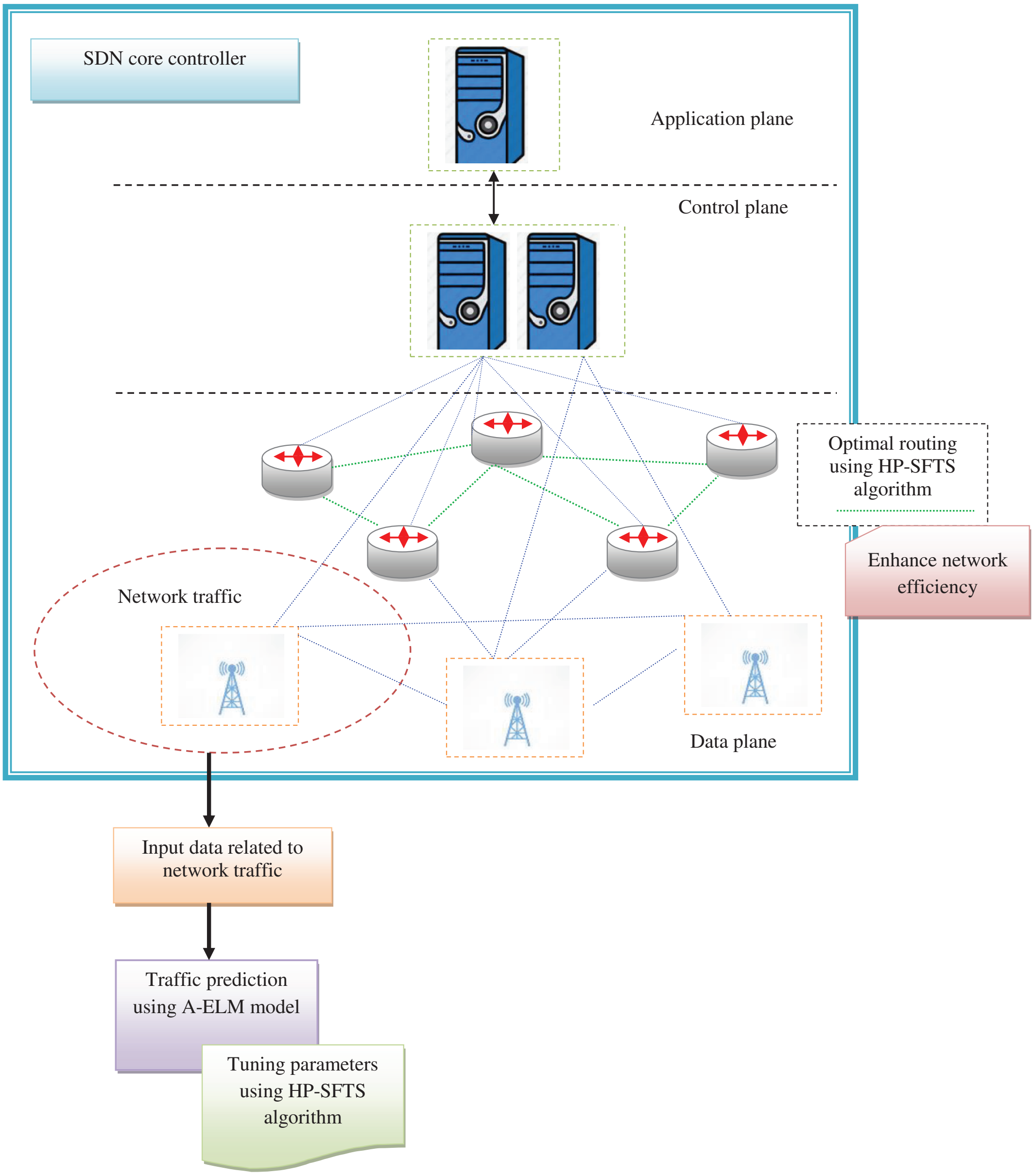


**FIGURE 1** | Schematic diagram of proposed traffic prediction and multipath routing in SDN using hybrid algorithm.

To overcome these drawbacks, the two algorithms are hybridized, where the final position is computed to return the optimal values. Thus, the new formulation in the proposed HP-SFTS is presented in Equation (1).

$$FiP = OldPn + \frac{Std(pos1, pos2)}{50} \tag{1}$$

Here, the position of previous iteration is known as the old position and it is indicated using $OldPn$. Further, the position obtained from SFOA is marked by $pos1$ and $pos2$ specifies the acquired position of TSA. Hence, the conventional algorithms are elucidated as below.

SFOA [31]: The sheep is a mammal species that inspires this nature-based algorithm. The core idea of this algorithm is based on the grazing behavior of sheep. Thus, the algorithm consists of two main phases: the grazing phase (graze activity) and the moving phase, which involves determining sheep locations, following the shepherd's commands, and moving sheep toward the best agents. Goats are also included in the group of agents. The mathematical model that describes the SFOA is given as follows.

*Population and iteration consideration*: Here, the input population is taken as the sheep and its total count is marked by $S$. Further, the maximum iteration is identified by $M$. The 10% of the total iterations is used in each search process, where a random position is generated. This resultant position is compared with the previous value.

*Grazing condition*: Depends on the grazing condition, the SFOA uses either grazing or moving process. Hence, the condition is shown in Equation (2).

$$Mod\left(\frac{m}{M/50}\right) = 0 \;\; or \;\; (m \geq M) - 5 \tag{2}$$

Here, the current and maximum iteration count is signified by $m$ and $M$, and also the mathematical operator is given by $Mod$.

In the grazing phase, each agent grazes within its defined radius, allowing the sheep to search for a food source. Therefore, the grazing radius for both sheep and goats is estimated using Equations (3) and (4).

$$Gr_{\text{sheep}} = 0.001 \times (upB - lwB) \times I \tag{3}$$

$$Gr_{\text{goat}} = 0.1 \times (upB - lwB) \times I \tag{4}$$

The term $I$ is estimated in Equation (5).

$$I = 1 - \left({}^{m}/_{M}\right) \tag{5}$$

Based on the fitness, the local and global best position is upgraded. Thus, the new position is also obtained.

*Moving section*: During the movement phase, the shepherd uses the global position to instruct the sheep herds to reach the target. The movement process differs between sheep and goats, as described below.

*Sheep movement*: The iteration is divided into two categories. When the condition is met, three scenarios are introduced.

Movement is guided by the shepherd's instruction to reach the optimal position, as defined in Equation (6). Depending on the sheep's tendency, movement occurs based on its previous position, as shown in Equation (7). Finally, movement toward other sheep is described in Equation (8).

$$u_{shp1,1} = (1 - I) \times P \times rd(1, S) \times \left(Q_{GBt} - Q\right) \tag{6}$$

$$u_{LBt,1} = P \times rd(1, S) \times \left(Q_{LBt} - Q\right) \tag{7}$$

$$u_{\text{other},1} = P \times rd(1, S) \times \left(Q_{RSp} - Q\right) \tag{8}$$

In the above all equation, the current position, global best, and local best position is declared as $Q$, $Q_{GBt}$, and $Q_{LBt}$, respectively. Further, the random position for sheep is given as $Q_{RSp}$. Term $S$ defines the dimension of the problem variable and $P$ is computed by Equation (9).

$$P = 3 \times rd \tag{9}$$

When the condition $I \leq 0.3$ satisfies, the position is revised for another sheep is mentioned in Equation (10).

$$u_{shp1,1} = P1 \times (1 - I) \times \left(Q_{GBt} - Q\right) \tag{10}$$

Goat movement: It also contains two conditions: in the first scenario as $I > 0.7$, the best position is obtained and it is given in Equation (11).

$$\begin{aligned} u_{shp1,2} &= rd(1, S) \times \left(Q_{GBt} - Q\right) \\ u_{LBt,2} &= (1 - I) \times 2 \times rd(1, S) \times \left(Q_{LBt} - Q\right) \end{aligned} \tag{11}$$

Moreover, when the condition as $I \leq 0.7$, the goat position is acquired via Equation (12).

$$u_{shp2,2} = (1 - I) \times 2 \times rd(1, S) \times \left(Q_{GBt} - Q\right) \tag{12}$$

Hence, the position $pos1$ is attained used for final updating.

TSA [32]: Tunicates are a species that are pale blue in color and cylindrical in shape, with one end open and the other end closed. Each tunicate agent can draw water from the sea, which then produces jet propulsion through the open end. Due to this fluid-driven motion, tunicates can move around the surface of the ocean. Here, the main objective is to find food sources or prey in the sea. Since tunicates lack prior knowledge about the location of food, they use two mechanisms namely swarm intelligence and jet propulsion to locate it. The TSA algorithm is derived using the following three steps.

*Conflicts avoidance among tunicates*: In order to achieve this, the vector variable $\vec{V}$ is considered for computing the new position for tunicates. It is shown in Equation (13).

$$\vec{V} = \frac{\vec{G}f}{\vec{S}f} \tag{13}$$

Here, the gravity and social force is indicated by $\vec{G}f$ and $\vec{S}f$, respectively. The term $\vec{G}f$ is expressed using the Equations (14) and (15).

$$\vec{G}f = d_2 + d_3 - \vec{A}f \tag{14}$$

The water flow advection is noted as $\vec{A}f$ and it is calculated using Equation (15).

$$\vec{A}f = 2 \cdot d_1 \tag{15}$$

In Equations (14) and (15), the random numbers are varied from 0 to 1 that is given in $d_1$, $d_2$ and $d_3$. Furthermore, $\vec{S}f$ is formulated in Equation (16).

$$\vec{S}f = \left[C_{mn} + d_1 \cdot C_{mx} - C_{mn}\right] \tag{16}$$

Here, the minimum and maximum speed to make the interaction represents in $C_{mn}$ and $C_{mn}$, which is fixed as the value of 1 and 4.

*Moving toward the best neighbor agents*: After the conflict is removed, the tunicates are moving to the nearest agents. It is shown in Equation (17).

$$D\vec{i} = |\text{P}\vec{r} - rd \cdot \vec{N}(t)| \tag{17}$$

The above equation is used to determine the distance between the tunicates and prey. Here, the current iteration and random value is noted as $t$ and $rd$, correspondingly.

*Converge toward the best agent*: The tunicate population manages the position to reach the best agent, given in Equation (18).

$$\vec{N}\left(t'\right) = \begin{cases} \text{P}\vec{r} + \vec{V} \cdot D\vec{i} & \text{if } rd \geq 0.5 \\ \text{P}\vec{r} - \vec{V} \cdot D\vec{i} & \text{if } rd < 0.5 \end{cases} \tag{18}$$

**ALGORITHM 1** | HP-SFTS.

Assume the input population
Fix the total iteration count
Do while $m < M$
  **SFOA optimization**
  Grazing condition
  Sheep movement is given in Equations (6), (7), and (8)
  Goat movement is obtained via Equation (11) and (12)
  **TSA Optimization**
  Conflicts avoidance is done
  Moving is happened by Equation (17)
  Position is upgraded using Equation (19).
  **Suggested HP-SFTS**
  Final position *FiP* is acquired through Equation (1)
  End the while loop
Obtains the best value

Finally, based on the swarm behavior, the final or optimal position is acquired using the Equation (19).

$$\vec{N}(t+1) = \frac{\vec{N}(t) + \vec{N}(t+1)}{2 + d_1} \tag{19}$$

Therefore, the position *pos*2 is achieved by the above equation. The pseudo code of suggested HP-SFTS is given in Algorithm 1.

The flow chart diagram of HP-SFTS is given in Figure 2.

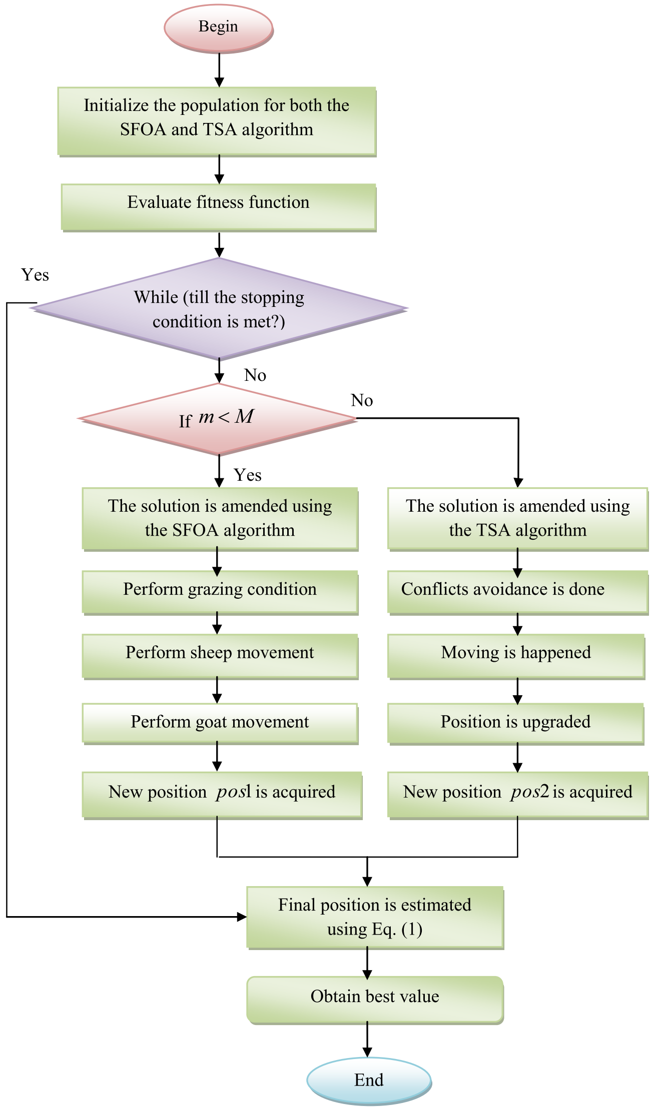


**FIGURE 2** | Flow chart of HP-SFTS algorithm.

## 4.2 | Extreme Learning Machine

ELM [33] is an essential learning model used for prediction, classification, and recognition tasks. For our objective, ELM is employed to predict network traffic. Here, the raw data $T_n$ is fed into the ELM, which is processed through several layers. Compared to other networks, ELM has the potential to solve the back-propagation issue and enhance network efficiency. It also operates with certain weight factors that are updated each time to improve the results. The training samples are denoted as $\{a_m, b_m\}$ from $T_n$, where $m$ refers to the trained samples from 1 to $M$. The derivation of ELM is presented in Equation (20).

$$o_m = \sum_{y=1}^{Y} \chi_{ym} f\left(wt_y, bi_y, a_m\right) \tag{20}$$

Here, the weight among the hidden layer and $m$th output neuron is defined by $\chi_{ym}$ and the weight between "hidden layer neuron and input neuron is marked by $wt_y$," the bias term as $bi_y$ and total layers as $Y$. Finally, the activation function of network is performed in $f(\cdot)$.

Since the intent of ELM is to determine the optimal results, the weight matrix as $\left[\chi_1 \ \ \chi_2 \cdots \chi_Y\right]^R$ based on the true condition as formulated using Equation (21).

$$\|o - b\| = \min_{\chi} \|o - b\| \tag{21}$$

Here, the Euclidean distance is calculated by $\|\cdot\|$ and $b = \left[\chi_1, \cdots, \chi_M\right]^R$. The output weight matrix is evaluated using Equation (22).

$$\hat{\chi} = F^{+} \cdot b \tag{22}$$

Lastly, the predicted output of the ELM model is acquired via Equation (23).

$$b = \sum_{m=1}^{Y} \hat{\chi} \cdot f\left(wt_m, bi_m, a\right) \tag{23}$$

Therefore, the network traffic is predicted and evaded to perform the better routing. Figure 3 shows the general structure of ELM for traffic prediction.

## 4.3 | Adaptive ELM for Traffic Prediction

The novel A-ELM model is developed to predict network traffic using the adaptive concept of HP-SFTS. In conventional ELM, the model includes multiple hidden layers, which increase complexity and affect system robustness. Though it provides better and faster results, the large number of epochs can lead to performance degradation. To avoid such shortcomings, the parameters in ELM are optimally tuned using the HP-SFTS algorithm. Thus, the fitness function for A-ELM-based traffic prediction is illustrated in

Equation (24).

$$FF1 = \arg\max_{\{hn,ep,spe\}}\left[ay + \frac{1}{mae + mse + rmse}\right] \quad (24)$$

Term, the hidden neuron is noted as $hn$ ranges of [5, 255], epochs are marked by $ep$ contains the limit of [5, 50] and the steps per epoch size is varied from 500 to 1000, given as $spe$. In addition to this, the accuracy $ay$ is defined as close measurement of the expected values. It is modeled in Equation (25).

$$ay = \frac{Aps + Ang}{Aps + Ang + Bps + Bng} \quad (25)$$

"Here, the true positive and negative, then false positive and negative is specified by $Aps, Ang, Bps, Bng$, respectively." Further,

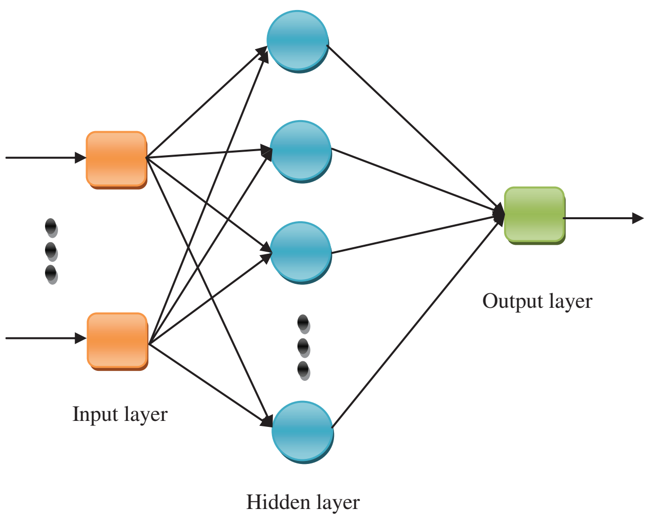


**FIGURE 3** | General structure of ELM for prediction.

the term $mae$ is the "Mean Absolute Error" used for calculating error "between the predicted and actual values," as shown in Equation (26).

$$mae = \frac{\sum_{j=1}^{J}\left|q_j - p_j\right|}{J} \quad (26)$$

Here, the true and observed value is annotated as $p_j$ and $q_j$ and also the total data samples is given as $J$. Similarly, for Mean Square Error and Root Mean Square Error are estimated using Equations (27) and (28).

$$mse = \frac{1}{J}\sum_{j=1}^{J}\left(q_j - p_j\right)^2 \quad (27)$$

$$rmse = \sqrt{\frac{\sum_{j=1}^{J}\left(q_j - p_j\right)^2}{J}} \quad (28)$$

The diagrammatic representation of novel A-ELM is given in Figure 4.

*Training of A-ELM method*: Initially, the input data $T_n$ is fed into the developed A-ELM model by considering the different layers such as the "input, hidden, and output layers." The training process of the A-ELM model involves "randomly initializing the weights and biases between the input and hidden layers." For ensuring better training performance, the input data is first given to the input layer, which then collects the specific features or attributes of the given data. The input layer is responsible for passing this information to the hidden layer. In this hidden layer, the weights and biases are randomly assigned in the developed model. During the training process, an excessive number of neurons in the model may lead to overfitting. Thus, the weights and bias vectors are assigned in the form of dot matrices to achieve accurate performance. Some specific features are generated in the

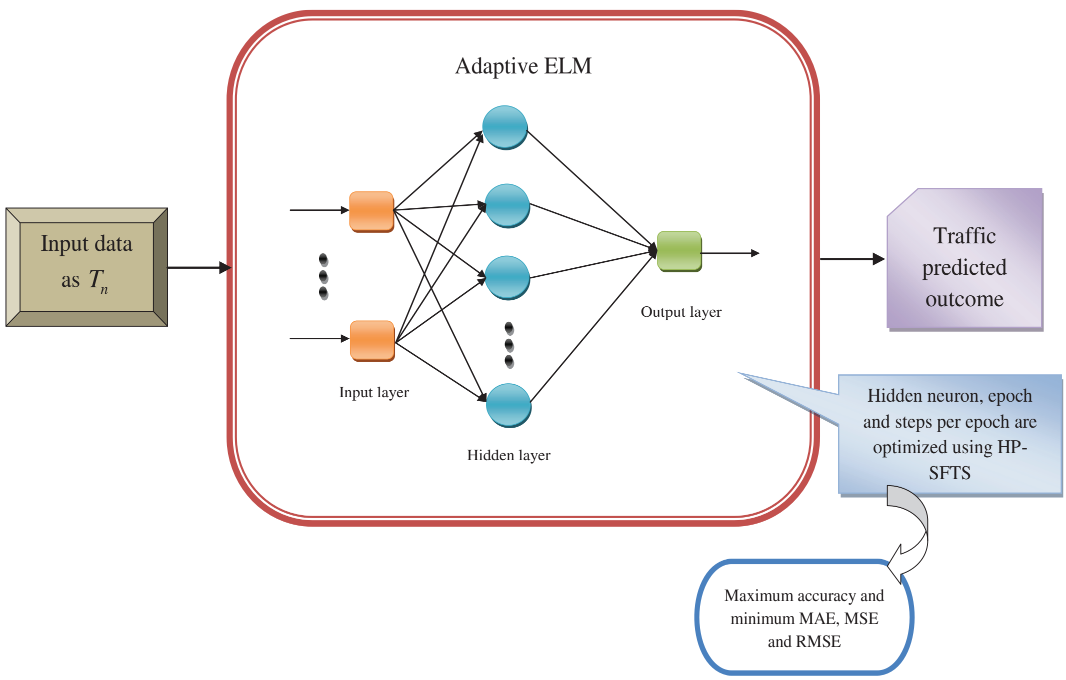


**FIGURE 4** | Depicts the diagram of A-ELM for traffic prediction with parameter optimization.

hidden layer. Finally, the output layer provides accurate prediction results. This process of the developed A-ELM model ensures higher reliability and delivers accurate outcomes in the traffic prediction framework.

For reliable performance, the parameters in the A-ELM model are tuned using the developed SFOA algorithm. The optimization is employed by considering the behavioral characteristics of sheep in the SFOA algorithm and tunicates in the TSA algorithm. In order to solve complex parameter issues, the research work adopts the HP-SFTS algorithm to achieve effective performance in the traffic prediction model. Here, the developed HP-SFTS algorithm is used to fine-tune the hyperparameters in the ELM model, such as the "number of hidden neurons $hn$, number of epochs $ep$, and steps per epoch $spe$, respectively." The tuning of hyperparameters in the model plays a significant role in managing complex parameters, which helps to enhance accuracy performance.

## 5 | Framework of Multipath Routing in SDN Using Optimal Path Selection by HP-STFS and Objective Function

### 5.1 | Multipath Routing

Naturally, the network consists of several devices or numerous nodes that can perform the transmission process. To achieve this, routing is the most requisite mechanism. Several paths are available to transmit the data packets from one place to another, the multipath routing is introduced. Some of the benefits of multipath routing are given below.

- It is more resistant to link failure since it uses multiple ways to transmit the data.
- While using a single path, the respective nodes can drop their energy or resources. This can be overcome during the multipath routing.
- It is also used to enhance network stability and sort the load balancing issues.
- The multipath routing can also able to tackle the large collection of data packets as it contains multiple paths.
- Through this mechanism, the SDN assists in increasing the throughput, packet delivery ratio and also decreasing the delay, path loss and so on.

### 5.2 | Optimization for Multipath Routing

In multipath routing, various ways are involved to find the shortest path for transmitting the data. When compared with the shortest path, the longest routing paths consume more energy, resources and utilize more nodes for performing data transmission. Due to such indetermination, the network misleads the communication process, performance degradation and less scalability. Thus, the shortest path is optimally chosen by influencing the concept of HP-SFTS. The network contains a varying number of nodes in which the developed HP-SFTS algorithm is performed for selecting the optimal path in the network for better transmission. By considering the developed HP-SFTS algorithm, the shortest path is initiated by considering the population of SFOA and the TSA algorithm based on several run times. The run times in the developed algorithm are repeated until it reaches the maximum number of iterations. Here, the network contains several number of nodes in which better data transmission takes place with the help of latency, delay, and throughput analysis. The network considers the large number of nodes, whereas some nodes are affected by heavy traffic, which affects the quality of data from the source to the destination. Heavy traffic affects the efficient route in the network might lead to information loss and show less energy in the network. The optimal route is selected from the source to the destination node using the HP-SFTS algorithm. When the node shows heavy traffic, it automatically selects the alternative path to transfer the data with a minimal amount of time. The selection of an optimal path enhances the network parameter performance and also stabilizes routing using the developed HP-SFTS algorithm.

*Minimization of network congestion*: Without any delay from the source and destination node, the network congestion is minimized to provide better quality of service in the network. The network congestion is highly minimized by distributing the traffic among multiple nodes instead of a single route, which helps to prevent link failures and bottlenecks, thereby increasing the network lifetime and throughput performance. Another strategy for minimizing network congestion is finding the optimal path from the source to the destination node with the help of the developed HP-SFTS algorithm. Thus, the fitness formula for multipath routing is formulated using Equation (29).

$$FF2 = \underset{\{pa\}}{\arg\max}\left[Thr + PDR + \frac{1}{Ly + PL + CRP}\right] \tag{29}$$

The term $pa$ denotes optimized shortest path, which is estimated using the number of nodes. The constraints taken in the objective function are described in Section 5.3. This derivation of the fitness concept, the optimal routing is performed by enhancing the throughput and packet delivery ratio with minimal delay. Based on this evaluation, the network congestion gets minimized in the traffic prediction and multipath routing framework.

The solution encoding diagram of multipath routing is mentioned in Figure 5.

### 5.3 | Description of Constraints in Objective Function

In Equation (29), different parameters are considered, that is elucidated below.

Throughput: It is annotated as $Thr$. It is referred to as the number of data packets that are transmitted over the path or link between the nodes.

Packet Delivery Ratio: It is annotated as $PDR$, which is the "ratio of delivered packets $X$ from source to destination to

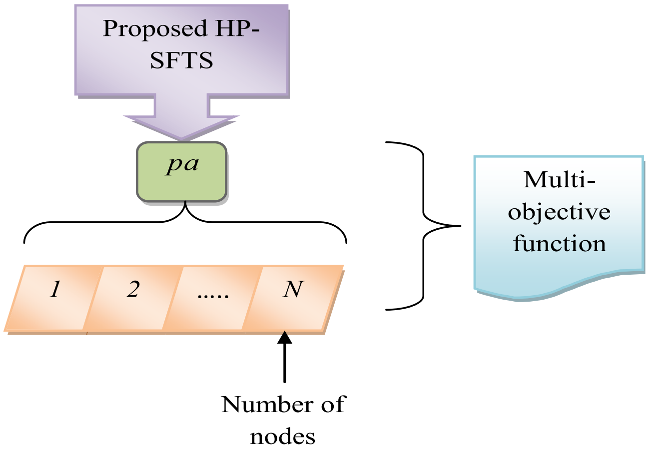


**FIGURE 5** | Solution encoding diagram for multipath routing.

the total number of data packets as $Y$". It is calculated by Equation (30).

$$PDR = \frac{X}{Y} \tag{30}$$

Latency: It is mentioned as $Ly$ that defines the time taken for sending the data or packets from the source node to the destination node.

Path loss: It is annotated as $PL$ used to determine the number of link failures in the network. The lower path loss helps to increase the efficiency.

Constraint Routing Problem: It is defined by the summation of such factors as denoted by $CRP$ [25]. It is given in Equation (31).

$$CRP = \sum_{b \in B} \sum_{a \in A_b} \varphi_a di_b \gamma_a \tag{31}$$

Here, $a$ is the path, $b$ signifies the routing flow and the traffic demand is marked as $di$.

### 5.4 | Experimental Setup

The proposed model was executed in Python, and it has estimated the extensive results. The proposed algorithm has considered the entire population as 10 and the maximum iteration as 100. The consideration of the existing model helps generate effective outcomes in the developed model. The rationale for picking the models and algorithms for comparative analysis in traffic prediction and multipath routing is the enable researchers to provide efficient outcomes. The consideration of each method and algorithm has its strengths and weaknesses, providing in-depth experimental analysis in the designed model to enhance the reliable performance. The experimental analysis of comparing the existing methods can impact the model's overall effectiveness in the traffic prediction and multipath routing framework. The comparative analysis by standard methods provides better insights to the researchers to predict the past and future contexts to boost the performance of the developed model. Existing algorithms such as Harris Hawks Optimization (HHO) [34], Arithmetic Optimization Algorithm (AOA) [35], SFOA [31] and TSA [32] were taken. Further, the different prediction models as Support Vector Machine (SVM) [36], Adaboost [37], Deep Neural Network (DNN) [38] and ELM [33], were considered to ensure the proposed model's effectiveness.

**TABLE 2** | Software Requirements of the developed model.

| Software requirements | Software version | Matlab R2020A |
|---|---|---|
| Hardware requirement | OS | Windows |
| | Version | 11 |
| | Processor | i3 |
| | RAM | 8 GB |
| | ROM | 500 GB |

**TABLE 3** | Simulation parameters of the developed prediction and multipath routing model.

| Parameters | Values |
|---|---|
| Number of nodes | [50, 100, 150] |
| Optimal election probability of a node | $p = 0.1$ |
| Topological area (m) | $300 \times 300$ |
| Total packets | 1000 |
| Number of nodes in the field | $n = 100$ |
| Initial energy (J) | $E_o = 0.3$ |
| Field dimensions $x$ and $y$ maximum (in m) | $xm = 100, ym = 100$ |
| $x$ and $y$ Coordinates of the Sink | sink.$x = 50$, sink.$y = 50$ |
| Percentage of nodes | $m = 0.1$ |
| Alpha | $a = 1$ |

*Dataset*: The traffic prediction data was collected from "https://www.kaggle.com/code/ijfezika/mobile-phone-activity-exploratory-analysis/input": Access Date: May 25, 2023. This dataset comprises the details of mobile devices used for predicting the network traffic. This dataset is resultant from real-world data, particularly from the Mobile Phone activity—exploratory analysis. This dataset involved a multi-source aggregation of news, social network, telecommunications, weather, and electricity data from Milan and Italy. Moreover, this dataset was produced by Telecom Italia in collaboration with other institutes like EIT ICT Labs, Northeastern University, etc. Hence, the collected data is represented as $T_n$, where the term $n$ specifies the total number of data points.

This data offers a rich source of insights that enhance the smart hotel experience by personalizing services, improving operational efficiency, and enabling targeted marketing and engagement. Also, it acts as a valuable source of information for understanding guest behavior and enhancing the smart hotel experience. An exploratory analysis of this data can reveal valuable patterns and correlations that can be used to optimize various aspects of the hotel's operations and guest experience. Table 2 depicts the software requirements of developed model. Also, Table 3 shows the developed model's simulation parameters.

## 6 | Results

### 6.1 | Convergence Analysis of the HP-SFTS Compared With Conventional Algorithms

Figure 6 depicts the convergence validation of the introduced algorithm by varying the number of iterations. Since the algorithm is performed over iterations, the performance is examined. The figures represent the convergence results with the variation in node counts in the network. Figure 6b shows the analysis when the network contains 40 nodes. At the 50th iteration, the cost function attains 16.1%, 12.9%, 61.2% and 45.1% of HHO, AOA, SFOA and TSA, respectively, which is higher than the proposed HP-SFTS. Thus, the less cost function aids in increasing the convergence rate of the algorithm to acquire impressive results.

### 6.2 | Performance Analysis of the Suggested Traffic Prediction Method

Figures 7 and 8 depict the performance assessment of the novel prediction model constrated with traditional algorithms as well as classifiers. This analysis is made by varying the different learning rates. Figure 8c illustrates the root mean square error (RMSE)

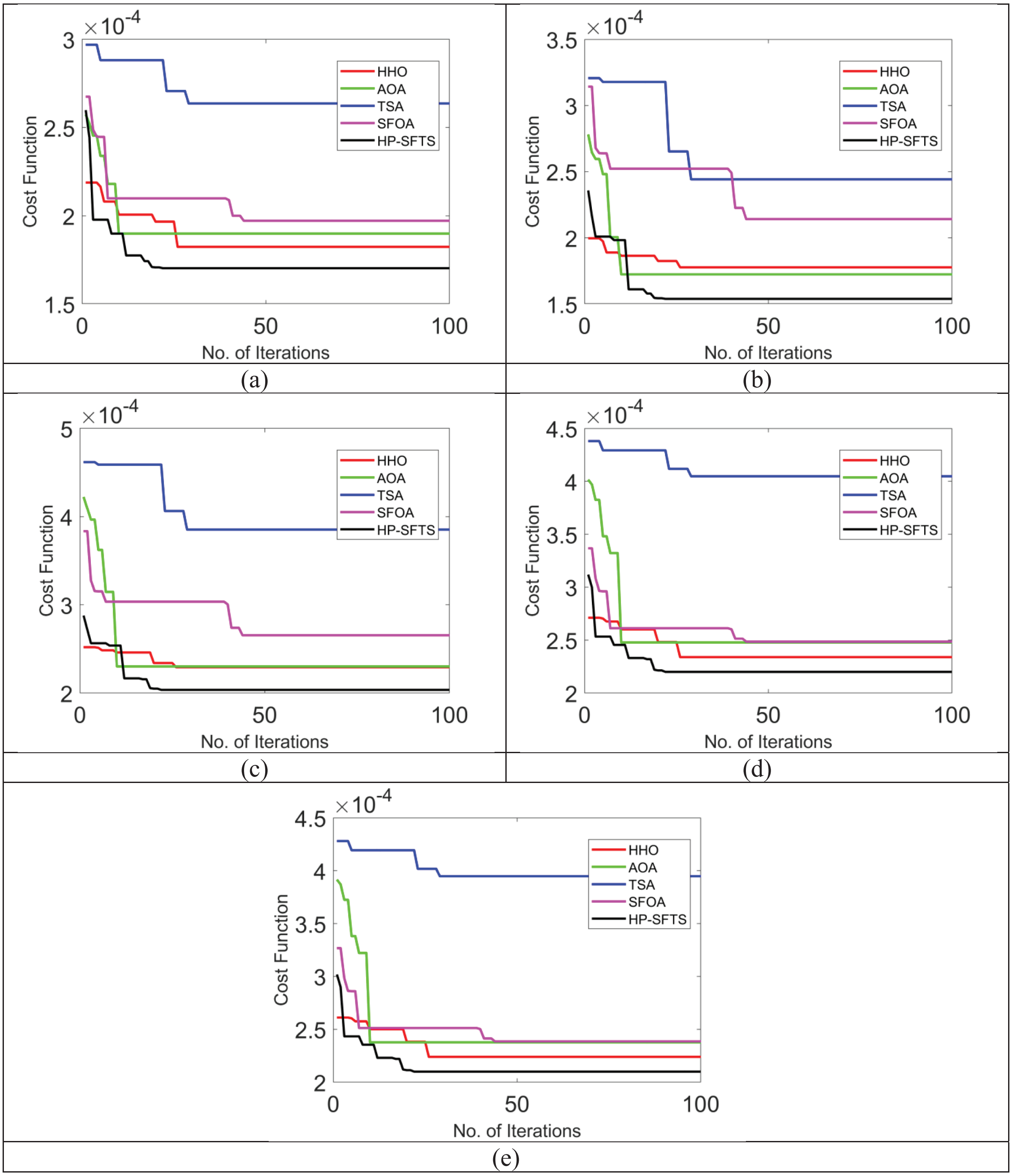


**FIGURE 6** | Convergence evaluation of the suggested HP-SFTS algorithm for traffic prediction and multipath routing in contrast with existing algorithms in terms of varying the network nodes as (a) 20, (b) 40, (c) 60, (d) 80, and (e) 100.

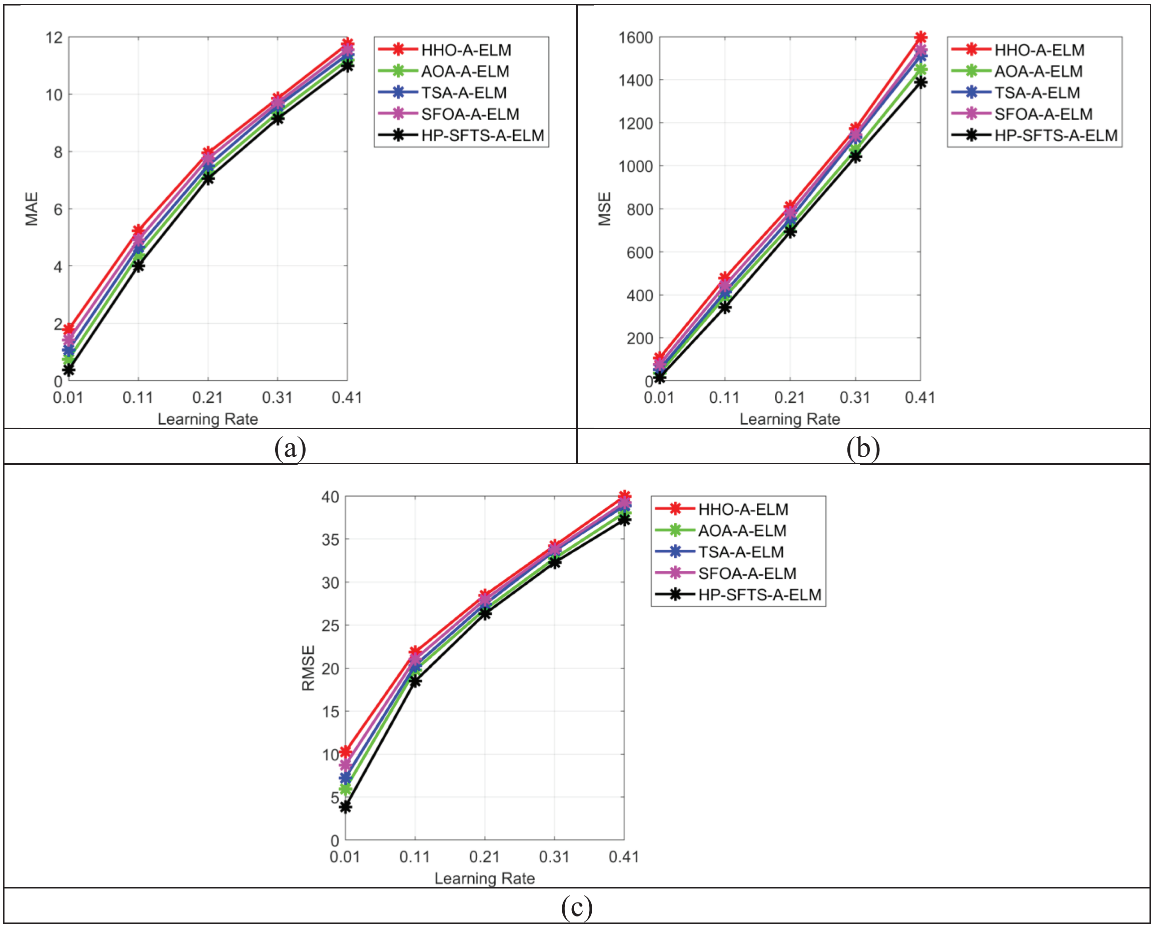


**FIGURE 7** | Performance estimation of the recommended traffic prediction and multipath routing in SDN in contrast with existing algorithms in terms of (a) MAE, (b) MSE, and (c) RMSE.

analysis compared over various classifiers. When the learning rate is 0.2, the RMSE of the proposed model attains less RMSE than 5.55%, 11.11%, 14.8% and 16.6% of SVM, Adaboost, DNN and ELM, respectively. Hence, the lesser error value ensures that the system has improved its performance.

### 6.3 | Evaluation for the Proposed Mechanism of Multipath Routing in SDN Compared With Diverse Algorithms

Figure 9 demonstrates the performance examination of the suggested routing process in contrast with different optimizations by changing the number of nodes. When the system considers 20 nodes, the path scalability is acquired as 64% of HHO, 40% of AOA, 88% of TSA and 63% of SFOA, which is lower than the novel HP-SFTS. Therefore, the system obtains better scalability, which enables the system to exploit effective transmission.

### 6.4 | Overall Analysis of the Recommended Traffic Prediction Model for Algorithm and Classifier Comparison

The overall effectiveness of the novel prediction model is given in Table 4. From table analysis, the error metrics like mean squared error (MSE), mean absolute error (MAE), and RMSE measures are validated among diverse classifiers and algorithm-based techniques. The decrease in error rate employs to enhance the model effectiveness in the traffic prediction and multipath routing model. The MAE of HP-SFTS-A-ELM is less than 6.9% of HHO-A-ELM, 1.9% of AOA-A-ELM, 3.6% of SFOA-A-ELM and 5.1% of TSA-A-ELM, respectively. Therefore, the system achieves less prediction error, which assists in effectively forecasting and evading the network congestion in SDN.

### 6.5 | Statistical Results of the Suggested Algorithm by Varying the Network Nodes

The statistical report for the suggested heuristic algorithm for ensuring the optimum performance is represented in Figure 10. This analysis is made by considering the different statistical measurements. When the nodes is 40, the mean value yields 12.5% of HHO, 11.25% of AOA, 63.7% of SFOA, and 44.3% of TSA, respectively, which is less than the novel HP-SFTS. Thus, the efficiency of the model reveals that it provides impressive results.

### 6.6 | Jitter-Based Performance Analysis of the Proposed Model

Jitter-based performance analysis of the introduced model is shown in Figure 11. This analysis is performed over various

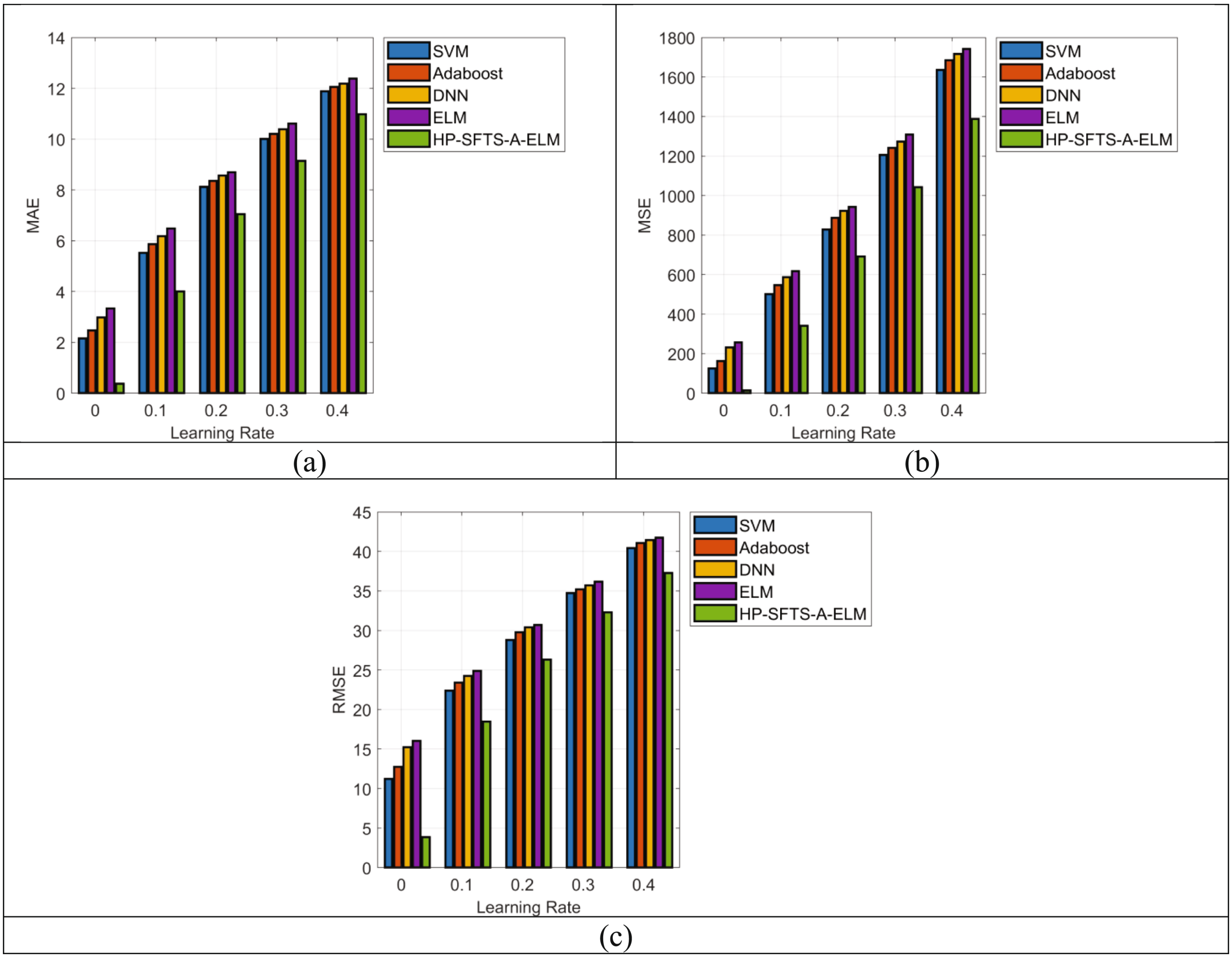


**FIGURE 8** | Performance evaluation of the recommended traffic prediction and multipath routing in SDN in contrast with existing classifiers in terms of (a) MAE, (b) MSE, and (c) RMSE.

existing approaches. Jitter analysis helps assess the effectiveness of multipath routing protocols in balancing traffic load across multiple paths. Here, the performance of the designed framework is higher than the existing approaches like HHO, AOA, TSA, and SFOA. Therefore, the result showed that the developed model handles larger data to offer better services to enhance the user experience in SDN to provide minimal delay.

## 7 | Discussion

The discussion section shows a brief elaboration of experimental findings in the developed model. Figure 6 specifies the convergence analysis of the developed model by considering various numbers of iterations. The minimal cost function is achieved due to the increasing number of iterations. The attainment of a minimal cost function helps the developed model to boost the convergence speed of the network. Considering Figures 7 and 8, the error-based analysis is evaluated in terms of diverse measures like MAE, MSE, and RMSE, respectively. The error-based analysis by both algorithms and classifier models. The minimization of error analysis helps the developed model achieve reliable performance to enrich the traffic prediction performance and provides optimal routing in SDN without any obstacles. Further, analysis is conducted with delay, latency, packet delivery ratio, packet loss, path reliability, path scalability, and throughput by considering various numbers of nodes (20, 40, 60, 80, and 100). For better data transmission, the developed model performs well in less delay and maximum throughput. Statistical analysis is performed in Figure 10. This statistical performance helps the developed model provide better decision-making performance in the traffic prediction model and shows optimal routing.

## 8 | Conclusion

This paper has presented the intelligent framework of traffic prediction and multipath routing over SDN. Initially, the data was gathered through the standard benchmark sources. Further, the input data was given to the A-ELM model for predicting the network traffic, where the hyperparameters were tuned by the proposed HP-SFTS. Further, the multipath routing efficiency was achieved by selecting the optimal paths, and it has also been used to formulate the objective function with different constraints. Lastly, the efficacy of the introduced scheme was evaluated with various metrics and compared with classical methodologies. When the network considered 80 nodes, the

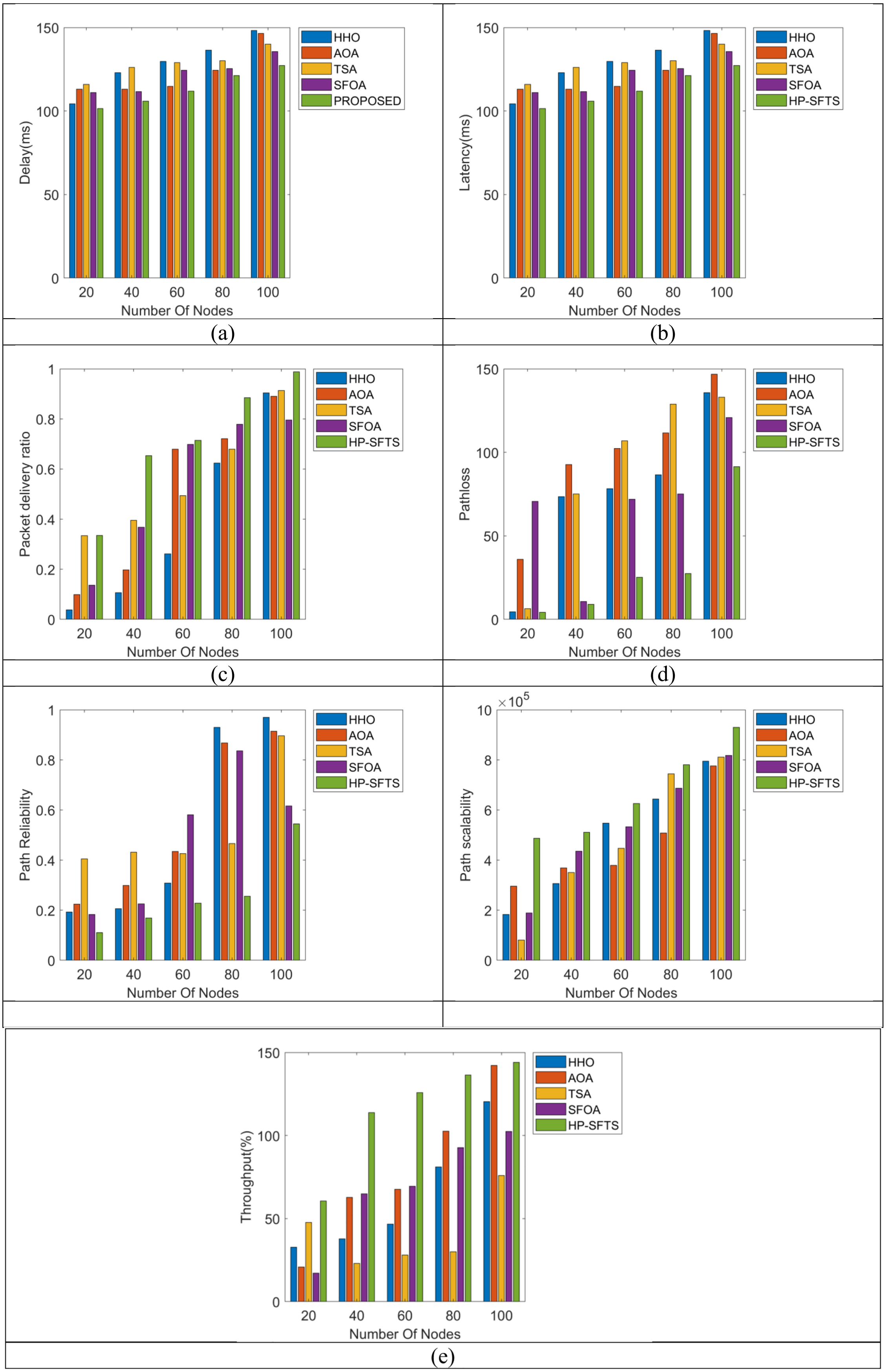


**FIGURE 9** | Convergence evaluation of the suggested HP-SFTS algorithm for traffic prediction and multipath routing in contrast with existing algorithms in terms of varying the network nodes as (a) 20, (b) 40, (c) 60, (d) 80, and (e) 100.

**TABLE 4** | Overall analysis of the proposed traffic prediction model in SDN compared with classical algorithms and deep learning models.

| Metrics | HHO-A-ELM [34] | AOA-A-ELM [35] | SFOA-A-ELM [31] | TSA-A-ELM [32] | HP-SFTS-A-ELM |
|---|---|---|---|---|---|
| Algorithm comparison | | | | | |
| MSE | 1596.2 | 1447.9 | 1511 | 1539.7 | 1387.6 |
| MAE | 11.743 | 11.188 | 11.377 | 11.547 | 10.979 |
| RMSE | 39.953 | 38.051 | 38.871 | 39.239 | 37.25 |
| Classifier comparison | | | | | |
| MSE | 1635.7 | 1684.9 | 1716.1 | 1742.2 | 1387.6 |
| MAE | 11.888 | 12.048 | 12.185 | 12.381 | 10.979 |
| RMSE | 40.444 | 41.048 | 41.426 | 41.74 | 37.25 |

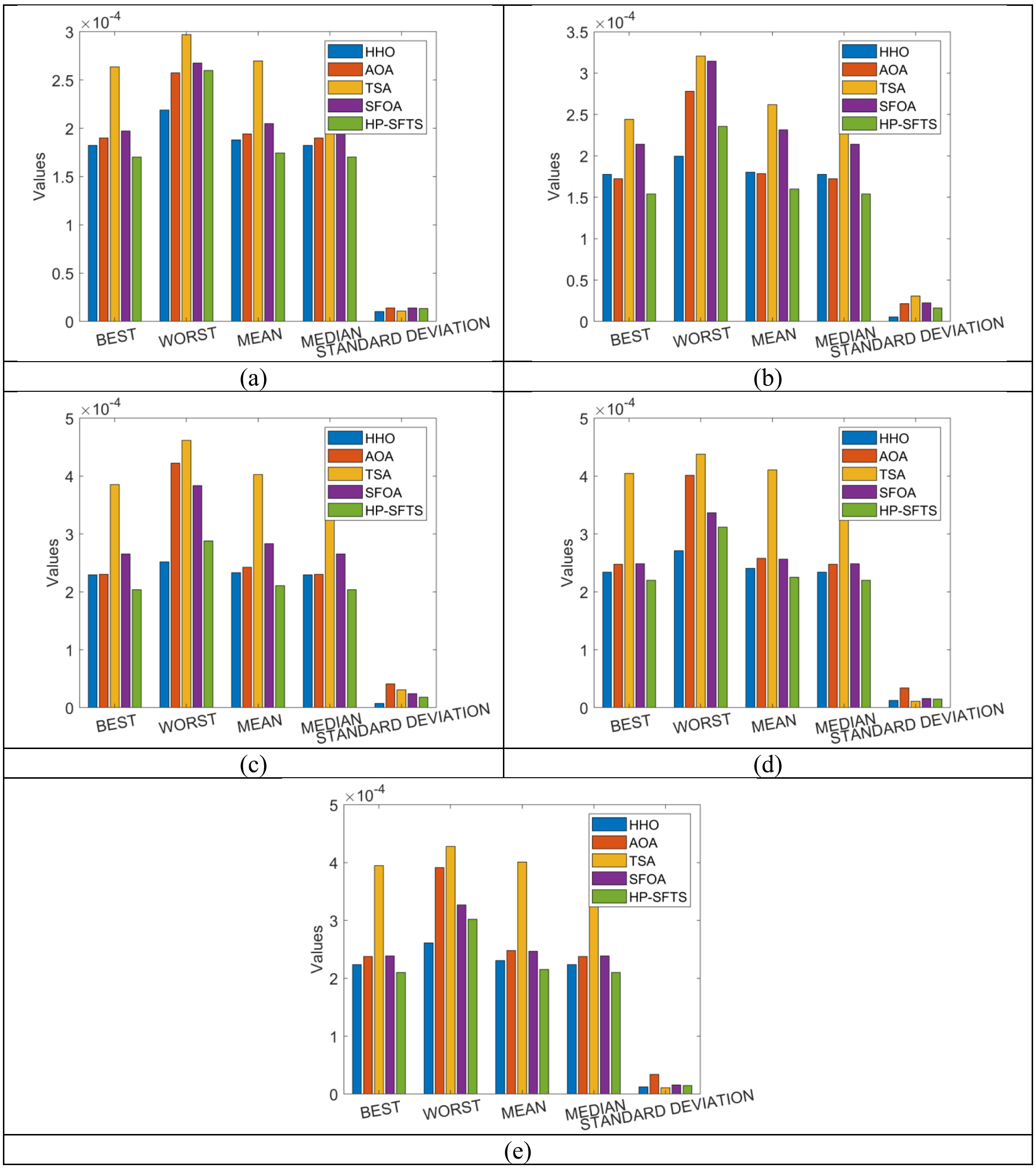


**FIGURE 10** | Statistical results of the proposed hybrid heuristic algorithm by different node counts as (a) node 20, (b) node 40, (c) node 60, (d) node 80, and (e) node 100.

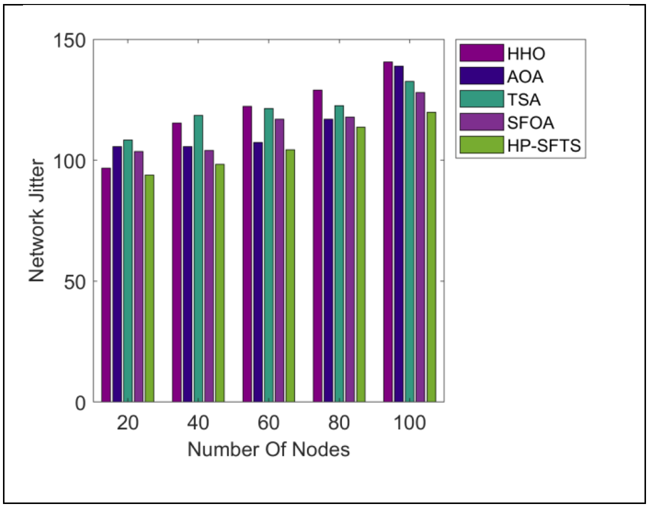


**FIGURE 11** | Jitter-based performance analysis of the proposed model.

throughput of the proposed work was attained as a higher value in contrast with 42.3% of HHO, 23% of AOA, 76.9% of TSA, and 34.6% of SFOA, respectively. Similarly, the prediction error was also obtained lesser than existing works. Therefore, the proposed work has shown that it has enhanced the system's efficiency in terms of diverse measures. By implementing result analysis, the developed model performs more effectively than the existing techniques. The analysis is validated with different numbers of nodes, whereas effective communication is performed without any interference or delay. The research works on multipath routing to boost the network reliability of the system and restrict the network congestion. While the developed model has shown promise, there are several areas that require further attention to enhance its robustness and effectiveness. Specifically, in dynamic network topology, the data quality issues are affected, which makes it difficult to provide robust and effective solutions in the traffic prediction model. For considering larger data, pre-processing is required to clean and format the data in an effective manner to handle missing values and outlier detection in complicated patterns. In a network management system, the traffic prediction and multipath routing framework play a vital role in selecting the optimal path for transferring the data to enhance network performance. Moreover, the developed model can be applicable for disaster recovery management, telecommunication networks, intelligent transportation systems and content delivery networks. By considering an intelligent transportation system, the navigation apps can reroute the vehicles to less crowded areas to reduce the traveling time and fuel consumption. In the telecommunication industry, traffic prediction and multipath routing help to prevent overloading to enhance the network performance. The consideration of these applications helps to transfer the efficient data across multiple paths to avoid bottlenecks. Also, the traffic prediction is widely performed in threat detection, resource management, dynamic traffic signal control, autonomous vehicle navigation, and network monitoring. By addressing the challenges associated with dynamic network topologies and data preprocessing, the developed model can be further refined and applied to create a more efficient, reliable, and secure network infrastructure.

*Complexity of the module*:

- Due to the intricate behavior of data, it considers non-linear relationships among the spatial and temporal factors that make the model more challenging and fail to capture the dependency and predict future patterns inaccurate.
- In a multi-path routing framework, it primarily focuses on discovering the multiple routes based on bandwidth, latency and reliability. Compared to single-path routing, multi-path routing is quite a challenging task as it is computationally intensive, which causes higher complexity.

*Lesson learnt in traffic prediction and multi-path routing*: A key lesson learned in traffic prediction and multi-path routing is accurately predicting the traffic by establishing a novel concept approach that is integrated with several constraints. Here, the adoption of the deep learning model has the ability to capture complex patterns and dependencies within the data that rely on past traffic patterns for reliable predictions. Especially when dealing with unexpected disruptions or changing conditions, the optimal path is selected in this research era. This optimal routing path helps the network communicate with each other and minimize network congestion. Also, the continuous monitoring and updation in the SDN model is analyzed in the deep learning model that reduces network overflow. On considering multipath routing, the developed model delivers better reliable performance in order to enhance fault tolerance to transmit the data in SDN. Distributing the traffic across various paths helps to prevent network congestion to improve network performance and throughput, especially in huge traffic networks. Overall, traffic prediction and multi-path routing often help to handle error handling mechanisms, which is crucial for maximizing traffic management.

*Future scope of the developed model*: Considering real-time data will be analyzed to provide accurate performance in the developed model. To eliminate outlier detection, the effective pre-processing technique will be focused on and implemented in the upcoming work. Experimental validation criteria will be further enhanced by considering linear forecasting models like ARIMA and Auto-Regressive Auto Regressive (ARAR) to predict the network traffic. A depth investigation is required by analyzing the numbers, locations, and the associated set of data plane switches will also be optimized by emerging advanced optimization algorithms. In addition, future research will be focused on incorporating additional performance metrics, such as jitter, into the fitness formula. Jitter refers to the variation in packet delay, which can significantly impact the quality of real-time applications like video conferencing, online gaming, etc.

## Data Availability Statement

The data underlying this article are available in https://www.kaggle.com/code/ijfezika/mobile-phone-activity-exploratory-analysis/input.

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