A Handoff Algorithm Based on Parallel Fuzzy Neural Network in Mobile Satellite Networks

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Abstract—In the next generation Internet, satellite will play a vital role in ensuring Always-Best-Connected, where handoff is essential. In view of the existing problems of satellite network handoff, for instances, long handoff delay and unnecessary handoffs, this paper proposes a method based on a parallel fuzzy neural network handoff algorithm. This method adopts parallel inputting modules and takes into consideration various factors which influence the overall performance. And it is able to adjust membership functions and decision rules to realize smooth handoff. This algorithm, with its good adaptability and learning ability, result in a better performance than traditional handoff algorithm in the aspects of reducing the system delay, blocking rate and average handoff times, and improving the system efficiency, leading to fast smooth handoff. In addition, it can also bring extra benefits of traffic equilibrium.

Index Terms—Satellite networks, fuzzy neural networks, smooth handoff, multi-factor decision

I. Introduction

Satellite networks are developed towards the integration of communication systems in the space, in the sky and on the earth. The integrated satellite communication system in the space-based part consists of satellite network. Satellite networks are characterized by wide coverage, multi-service, and large capacity. On the other hand, the complex satellite link, high latency and high dynamic bring the difficulties in the design of the handoff process and the handoff strategy. Handoff aims to bring continuous uninterrupted reliable service to users. The handoff delay and the numbers of handoff have dramatic effects on the system, which will further affect the communication capacity utilization. Geostationary satellite, for example, is about 36,000 km distance far from the ground. A simple calculation shows that the one-way wireless signal transmission delay between the ground mobile terminal and satellite is about 125 ms. However, signal transmission of a ground mobile communication system, taking the long-term evolution (LTE) system for example, costs only 0.33 ms from the terminal to the base station within a cell of 100 km maximum coverage radius. In terms of handoff times, taking 1,000 km of LEO satellite for example, a handoff performs in 8 to 9 minutes. Due to frequent handoff, blocking rate is so high that it results in system efficiency decline. Under the high handoff frequency, excellent handoff strategy is obvious excellent.

The remainder of this paper is organized as follows. Section II reviews related work. Section III presents the design of the proposed algorithm. Section IV and Section V describes the details with respect to two aspects. Section VI shows numerical results to evaluate the performance of the algorithm. Section VII concludes this paper.

II. Relative Work

This section of the paper presents an overview of recent work in the satellite handoff methods and vertical handoff methods.

Handoff process can be split into three parts [z-26]: (1) Handover information gathering, (2) Handover decision, and (3) Handover execution. Among them, the handover decision phase is one of the most critical processes during the handover. To make an accurate decision, this phase takes advantage of algorithms that, considering the information available, perform an evaluation process in order to obtain the best choice for handover execution. This phase is also known as system selection, network selection [1].

The handoff decision algorithm can be divided into 3 types that are single target policy algorithm, multiple attribute decision making algorithm (MADM), and other mathematical algorithm.

The single target policy algorithms are based on power, user density, location information or others [2], [3]. These algorithms always set some threshold and hysteresis to prevent ping-pong handoffs [4], which are simple to realize. Nevertheless, they are not suitable for the complex environment of satellite networks with only considering one factor. Power based handoff algorithm easily causes frequent handoff, user density based algorithm and location information based algorithm are poor in accuracy.

MADM algorithms include Simple Additive Weight (SAW) [5], Multiplicative Exponent Weighting (MEW) [6], Analytic Hierarchy Process (AHP) [7], Technique for Order Preference by Similarity to Ideal Solution (TOPSIS)

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[8], [9], Grey Relational Analysis (GRA) [10] and Preference Ranking Organization METHods for Enrichment Evaluations (PROMETHEE) [11]. The main problems of MADM algorithms are the unreliable network selection caused by dependency on attribute normalization and a rank reversal problem [12] during the removal and insertion of the network in the network selection list. Although there are some solutions for these problems such as taking Closeness Index (CI) or utility matrix to replace the normalization method and taking the absolute ideal solution to replace the relative ideal solution [13], they go against with the original ideas of the MADM algorithms.

The other mathematical algorithms contain game theory based handoff algorithms [14], fuzzy logic based handoff algorithms, neural network based handoff algorithms [15], [16], Markov Chain based algorithms [17] and others.

There are also some combination of the MADM algorithms and the mathematical algorithms, for example, the fuzzy-AHP method [18].

As stated in [19], multiple-parameters-based algorithms should be used to select the information, in order to take the most of the context environment. So the latter two sort of algorithms are considered in the satellite algorithms firstly.

At present, the researches on satellite handoff based on the fuzzy neural network and fuzzy logic handoff are rare. There are certain researches about fuzzy logic handoff on vertical handoff (VHO) [20]-[22]. Within these researches, two main problems exist. The first one is the input parameter design problems, which is difficult to measure or obtain. Such as in paper [20], it takes the user's movement speed as the input. However, this is difficult to estimate since the velocity vector of ST change quickly. The second one is that some researches are too dependent on expert experience [21], [22], and lack of adaptive adjustment process, which makes the algorithms difficult to adapt to the complex changes in the environment, so that the robustness is poor. In order to address the above problems, this paper put forward a Parallel Adaptive Fuzzy Neural Network Handoff Algorithm (PA-FNNHA), which is based on the traditional fuzzy logic algorithm, and contains feedback neural network to adjust the parameters of the fuzzy membership functions and inference rules.

III. The Design of Parallel Fuzzy Neural Handoff Algorithm for Satellite Communications

Handoff process includes phases of measure control, measure report, handoff decision and handoff execution. This paper mainly considers selection strategy of target satellite in the 3-rd phase. The following parts mainly discuss the selection strategy of a target satellite.

The selection of target satellite is ascribed to a problem of multiple object decision making (MODM) [23]. The final purpose of handoff decision is to choose a suitable target satellite. Decisions are made on the basis of terminal receiving signal intensity, available bandwidth, delay, network load, terminal position, and so on.

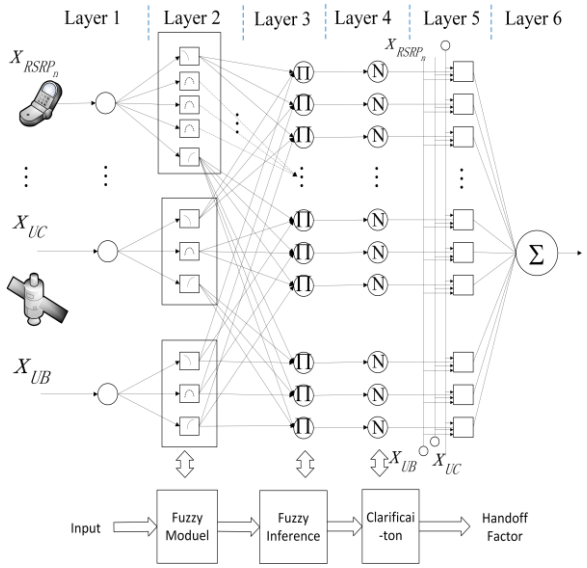


Fig. 1. PA-FNNHA neural network structure

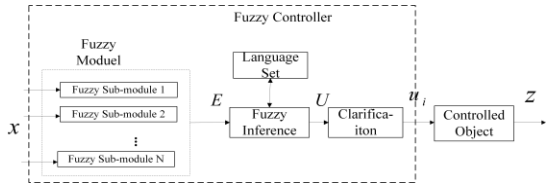


Fig. 2. PA-FNNHA handoff control model

The paper adopts parallel fuzzy neural network control algorithm, and comprehensively considers network and terminal information to make handoff decision. The structure of the proposed algorithm PA-FNNHA is shown in Fig. 1, which can functionally equivalent to a Takagi-Sugeno-Kang (TSK) fuzzy system.

The neural network realizes a fuzzy controller except for training function. The fuzzy controller block diagram is shown in Fig. 2.

An accurate vector $\boldsymbol{x}$ is passed through the fuzzy controller to produce output acutance variable U_i to control object. The fuzzy controller consists of a fuzzy module, a fuzzy inference module, a language set module and a clarification module (also known as defuzzy module).

The fuzzy module takes parallel structure and different elements of the inputting vector are passed through different fuzzy sub-modules which consist of corresponding membership functions. The fuzzy inference module is typically come from expert experience. The language set is the natural language expression of fuzzy attributes. The clarification module converts fuzzy values to accurate values to control the controlled object easily. According to the module in the Fig. 1, the proposed PA-FNNHA algorithm principle will be descripted in details.

IV. The Process of Fuzzy Control

A. Getting Input

The choice of input determines the feasibility and accuracy of fuzzy neural network algorithm. For instance, in the paper [24], the improper selection of input leads to the decline of the algorithm's performance. Fig. 3 shows the satellite motion.

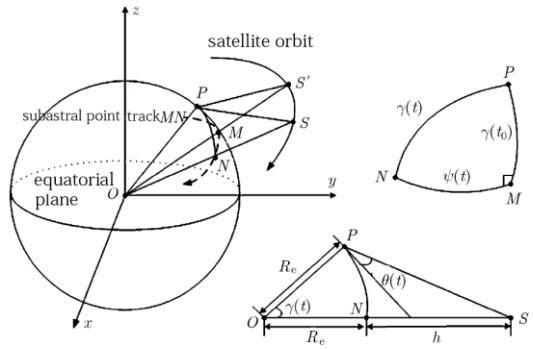


Fig. 3. Satellite under the direction of motion vector with the stars point and terminal vector angle

TABLE I: INPUT NAME-SYMBOL CHECKLIST

Measurement Entity	*Measured Variable Name*		*Variable Symbol*
Terminal	Reference Signal Receiving Power (RSRP)		X_{RSRP}
	The mobile location(MLC)	Predictive Estimation Service Time (t)	X_t
Satellite	Sub-star point Location (SLC)		
	Load (L)		X_L
	User Density (UD)		X_{UD}
	Usable Bandwidth (UB)		X_{UB}

Table I shows the selected input variable and the name-symbol checklist. The paper selects two terminal measured parameters, four satellite statistical parameters. What need to be aware of are that the mobile location coordinates, and sub-satellite point position coordinates information are not direct input. Instead, they are used to estimate service time by computing.

We have [25]

$$X_t = \frac{1}{\omega}\arccos\left(\frac{\cos\gamma_0}{\cos\gamma_m}\right) \tag{1}$$

where $\omega = (\omega_s - \omega_e \cos i)/2$ is an attribute of the satellite constellation; ωs and ωe are the angular velocity of satellites and the angular velocity of the earth's rotation, respectively. Parameter γ0 in (1) represents the earth central angle corresponding to the minimum elevation angle θ_0

$$\gamma_0 = \arccos\left(\frac{R_e}{R_e + h}\cos\theta_0\right) - \theta_0 \tag{2}$$

R_e is the radius of the earth. h is the orbit height of the satellite. The variable γ_m represents the minimal value of angular distance between the satellite's sub-star point location (SLC) and the mobile location (MLC). It has been shown that γ_m can be used to interpret user's location with respect to the serving satellite footprint [26]. In virtue of Eq. (1), it turns out that random coverage times in any pass of a LEO satellite stems from random values of the variable γ_m [7].

What needs be pointed out is that too much input will reduce the sensitivity of the handoff trigger, leading to radio link failure (RLF), this algorithm select the five key inputs under test.

In order to remove the impact of that different inputs have different dimensions, need to normalize on the domain as (3).

$$x_{nor} = \frac{x - x_{\min}}{x_{\max} - x_{\min}} \tag{3}$$

B. Fuzzy Language Set

Fuzzy control is based on the natural language, using brain logic to distinguish the input. The amounts of fuzzy subsets should be selected appropriately. The fuzzy logic reasoning rules grow at a geometric rate with the increased amounts of fuzzy subsets. For more influential attributes to the handoff result, this paper adopts five grade division while three grade division are adopted on the less influence factor. Such difference can reduce the complexity of the handoff, as well as reflect the network status.

As shown in (4), the selected language sets are listed below, including reference signal receiving power (abbr. RSRP), estimated service time (abbr. t), satellite load (abbr. L), user density (abbr. UD), and usable bandwidth (abbr. UB). The output value (abbr. O) also needs to be fuzzy in order to facilitate the establishment of the inference rules.

T (RSRP) = {High, Slightly High, Medium, Slightly Low, Low} = {H, SH, M, SL, L}

T (t) = {Long, Slightly Low, Medium, Slightly Short, Short} = {L, SL, M, SS, S}

T (L) = {Large, Medium, Small} = {L, M, S}

T (UD) = {More, Medium, Less} = {More, M, Less}

T (UB) = {Large, Medium, Small} = {L, M, S}

T (O) = {Certainly Yes, Likely Yes, Probably, Likely No, Certainly No} = {CY, LY, P, LN, N} (4)

C. The Selected Membership Function (MF) in the Algorithm

Membership function is one of the most important concepts in a fuzzy control system. The scheme of this paper is to preliminarily determine the rough membership function firstly, and then gradually modify and improve by "learning" and practical test. Although the trapezoidal/triangle membership function equation is simple and has the advantage of high calculation efficiency, its non-differential features make it difficult to learn in the neural network. The paper adopts differentiable and derivational Gaussian membership functions, such as

$$\mu_A(x_i) = \exp\left[-\frac{(x_i - m_i)^2}{\sigma_i^2}\right] \tag{5}$$

The number of elements of language set is equal to the number of membership function. Fig. 4 and Fig. 5 list 2 of the 5 membership function cluster curves with uniform distribution.

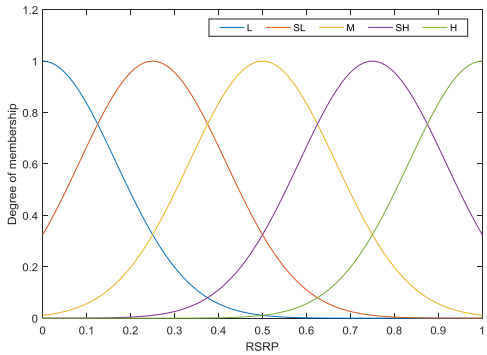


Fig. 4. The initial membership functions of RSRP

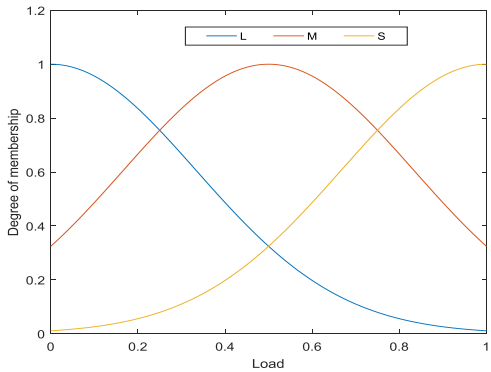


Fig. 5. The initial membership functions of load

D. The Clarification

The output of the inference module cannot be directly applied to a controlled object. It needs to be further "translated", namely clarification. The clarification module will translate the fuzzy value into a precise value, we can compare the values of all candidates to deal with which satellite to be selected. Gravity method takes the gravity center of outputs of inference as the final output of the system, namely

$$Z_0 = \frac{\int_z z\mu(z)dz}{\int_z \mu(z)dz}, \quad z \in Z \tag{6}$$

For discrete domain, there is

$$Z_0 = \frac{\sum_{i=1}^{N} z_i \mu(z_i)}{\sum_{i=1}^{N} \mu(z_i)}, \quad z \in Z \tag{7}$$

Compared to the maximum membership degree method, gravity method is more precise and more sensitive to the change of the system input.

V. The Process of Nerual Networks Training

A. Adaptive Neural Network

The structure of the proposed algorithm PA-FNNHA is shown in Fig. 1 which can make the membership functions and rules adapt to the changes in the environment. This is in sharp contrast to the traditional fuzzy logic handoff algorithm. The PA-FNNHA algorithm can adjust rules and membership functions according to the historical data of adaptive tracking area.

Early adaptive fuzzy logic structure was put forward by Jang, which uses the improved artificial neural network training algorithm to realize the optimization of fuzzy inference system. Most of the early traditional Fuzzy Logic Handoff (FLH) algorithm is based on a Mamdani model. Although Mamdani model is simple in design, the computation efficiency is poor.

The PA-FNNHA algorithm proposed in this paper adopts a TSK fuzzy model which provides more efficient computation. The if-then rules of TSK model are as follows.

$$\begin{aligned} &Rule\ i: If\ (x_{RSRP}\ is\ A_1)\ and\ ...\ and\ (x_{UD}\ is\ B_1)\ and\ (x_{UB}\ is\ C_1) \\ &then\ f(i) = p_i x_{RSRP} + \cdots q_i x_{UD} + r_i x_{UB} + S_i \qquad (1 \le i \le m) \end{aligned} \tag{8}$$

The equation (8) despites the *i-th* rule, where p_i, q_i, r_i *and* s_i are the consequent parameters, which are as weighting parameters used in the training process, corresponding to the *i-th* rule. *m* is the amount of the rules. In order to facilitate the follow-up analysis, we rewrite (8) as (9).

$$\begin{aligned} &Rule\ i: If\ (x_1\ is\ F_1^i)\ and\ ...\ and\ (x_r\ is\ F_r^i) \\ &then\ f(i) = \alpha_0^i + \alpha_1^i x_1 + \cdots + \alpha_k^i x_k + \cdots + \alpha_r^i x_r \qquad (1 \le i \le m) \end{aligned} \tag{9}$$

where $F_j^i\ (j = 1, 2, \cdots, r)$ is a fuzzy set, $\alpha_j^i\ (j = 0, 1, 2, \cdots, r; i = 1, 2, \cdots, u)$ is a real-valued parameter, and $f(i)$ is the system output according to the *i-th* rule. The whole structure is shown in Fig. 1, divided into six layers.

The first layer: input layer. This layer is used to transfer the input of the system directly to the second layer, the nodes contain no function transformation. The total number of nodes of this layer is *N1=n* (n is the number of input attributes).

The second layer: fuzzy layer. This layer is applied to thebg t input fuzzy, and the node functions are the membership functions of the fuzzy system. This layer takes the Gaussian membership function and every node represents m_i (in this paper, m_i equals 3 or 5) membership functions corresponding to an input. The *j-th* membership function of the *i-th* input of the node is

$$\mu_i^j(x_i) = \exp[-(x_{ij} - c_{ij})^2 / b_{ij}^2] \quad i = 1, 2, \cdots, n \quad j = 1, 2, \cdots, m_i \tag{10}$$

In this equation, c_{ij} and b_{ij}, called the premise parameters, denote the center and width of Gaussian

membership function respectively. The values of c_{ij} and b_{ij} will be adjusted to optimize the neural network.

The third layer: the premise rule matching layer. The layer makes a full connection among the second layer nodes, which realizes the combination of the fuzzy set of the second layer as the equation

$$\omega_i = \prod_{i=1}^{n} \mu_i^k\left(x_i\right) \quad i = 1, 2, \cdots, m \tag{11}$$

where k is the sequence number of a membership function corresponding to the i-th input. The number of nodes is N3 ($N_3 = m = \sum_{i=1}^{n} m_i$).

The fourth layer: normalized layer. This layer achieves normalized output with coupling in this layer, as

$$\psi_i = \frac{\omega_i}{\sum_{i=1}^{m} \omega_i} \tag{12}$$

where the output is the normalized applicability of every rule, and the presence or absence of the connection weights indicates whether or not the rule is applicable.

The fifth layer: rule conclusion layer. This layer computes the latter part of the rule depicted in (9), and this layer achieves the following function. The number of nodes in this layer is N4 (*N4 = m*).

$$y_i = \psi_i f_i = \psi_i\left(\alpha_0^i + \alpha_1^i x_1 + \cdots + \alpha_k^i x_k + \cdots + \alpha_r^i x_r\right) \quad (1 \le i \le m) \tag{13}$$

where α_k^i is called consequent parameter.

Finally, in sixth layer, all of the signals are merged into one output signal, as

$$z = \sum_{i}^{m} \psi_i f_i \tag{14}$$

z is the output of the clarification and the handoff factor .

B. Training Process under the Handoff System

Training is divided into online and offline training. When the performance is lower than the acceptable threshold, online training will be triggered, or it will be triggered when it is in need which can guarantee the MFs and rules are optimal in most time. Offline training uses historical data, which also update the parameters when available. Training is used for calibrating the model, to guarantee the handoff is triggered under a coincident condition.

For the training of the premise parameters, both of the training methods use mixed steepest descent method and minimum mean square estimate to complete, which can achieve rapid convergence, and require less search operation. Error calculation uses

$$e = \frac{1}{2}\left(z_d - z\right)^2 \tag{15}$$

In the equation, z_d is the expected output of the networks, *z* is the actual output of the networks。*e* is the error between z_d and *z*. Hybrid training method is executed in each forward and back stage in every iteration, training update equations are

$$c_{ij}\left(k\right) = c_{ij}\left(k-1\right) - \beta \frac{\partial e}{\partial c_{ij}} \tag{16}$$

$$b_{ij}\left(k\right) = b_{ij}\left(k-1\right) - \beta \frac{\partial e}{\partial c_{ij}} \tag{17}$$

where c_{ij} and b_{ij} are the center and width of the membership function respectively. β is network learning rate. The training for the consequent parameters are described below.

Equation (13) can be written as follow.

$$Z = F \times \Psi \tag{18}$$

where

$$F = \left[\alpha_{10} \quad \cdots \quad \alpha_{m0} \quad \alpha_{11} \quad \cdots \quad \alpha_{m1} \quad \alpha_{1r} \quad \cdots \quad \alpha_{mr}\right] \tag{19}$$

$$\Psi = \begin{bmatrix} \psi_{11} & \cdots & \psi_{1n} \\ \vdots & \vdots & \vdots \\ \psi_{m1} & \cdots & \psi_{mn} \\ \psi_{11} \bullet x_{11} & \cdots & \psi_{11} \bullet x_{1n} \\ \vdots & \vdots & \vdots \\ \psi_{m1} \bullet x_{11} & \cdots & \psi_{mn} \bullet x_{1n} \\ \vdots & \vdots & \vdots \\ \psi_{11} \bullet x_{r1} & \cdots & \psi_{1n} \bullet x_{rn} \\ \vdots & \vdots & \vdots \\ \psi_{11} \bullet x_{r1} & \cdots & \psi_{11} \bullet x_{rn} \end{bmatrix} \tag{20}$$

Assuming the ideal output is $T = \left(t_1, t_2, \cdots, t_n\right)$, the relationship between Ψ and T is

$$Z = F \times \Psi \tag{21}$$

$$E = \left\| T - Z \right\| \tag{22}$$

Our objective is to find an optimal coefficient vector F^* that minimizes the error energy $E^T E$. In this paper, Regression Least Squares (RLS) method is used to determine the weight of F.

$$F_i = F_{i-1} + S_i \Psi_i^T \left(T_i - \Psi_i \Psi_{i-1}\right) \tag{23}$$

$$S_i = S_{i-1} - \frac{S_{i-1} \Psi_i^T \Psi_i S_{i-1}}{1 + \Psi_i S_{i-1} \Psi_i^T} \quad i = 1, 2, \cdots, n \tag{24}$$

The initial conditions are $F_0 = 0$ and $S_0 = \chi I$, S_i is the covariance matrix of the *i-th* observed data, Ψ_i is the *i-th* column in Eq. (20), F_i is the coefficient matrix after the *i-th* iteration, χ is a sufficiently large positive number, and I is a unit matrix.

When the amounts of sample data increases, the least squares method will gradually enter a saturated state and lose the adjustment ability. The paper uses a forgetting factor to make the newly added data have a larger weight to solve the problem, as

$$S_i = \frac{1}{\lambda}\left(S_{i-1} - \frac{S_{i-1}\Psi_i^T \Psi_i S_{i-1}}{\lambda + \Psi_i S_{i-1} \Psi_i^T} \right) \quad i = 1, 2, \cdots, n \tag{25}$$

where $0 < \lambda < 1$, and the smaller the λ, the faster the data is forgotten.

Under the training process above, the network can be optimized. Finally, it can optimize the output, thus providing more accurate handoff factor.

VI. Simulation Verification

The traditional handoff strategies will be compared with the PA-FNNHA method to demonstrate their respective advantages and disadvantages. The paper takes one-layer satellite network consisting of 48 satellites. The bandwidth and other parameters of the satellite system are set up according to Table II.

TABLE II: SIMULATION PARAMETERS

Parameters	***Specifics***
Operating bandwidth per ST(MHz)	10
Carrier frequency(GHz)	22
Fading model	Satellite Rice channel model
Number of Satellite	48
Parameters	***Specifics***
Number of Gateway	3
Orbit height	1000Km
Number of STs	1 in Simulation A, 100-1000 in Simulation B
Call arrival	Three calls per ST
Call duration	Random 1–30 min per call for each ST, based on exponential distribution
NCC transceiver power (dbW)	105

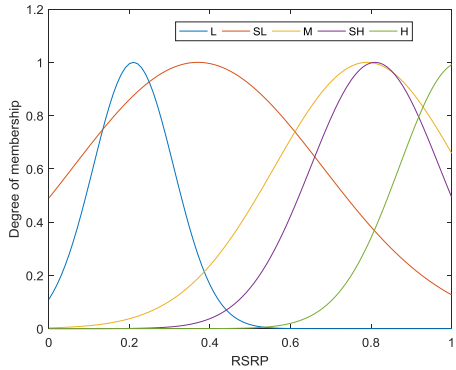


Fig. 6. Trained membership functions of RSRP

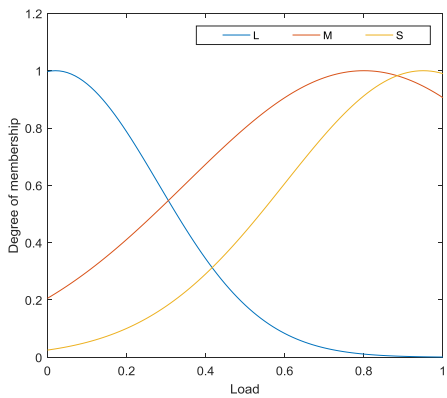


Fig. 7. Trained membership functions of load

The simulation takes Matlab+NS2 simulation tool to build an experimental platform for satellite network system. The following simulation of PA-FNNHA is based on the membership function presented in Fig. 6, Fig. 7 and other three optimized membership functions.

A. Simulation A: Instantaneous Throughput

There are two cases in simulation A. The simulation A compares five different handoff algorithms with one ST, including the FLH, LBH (Location Based Handoff), the proposed PA-FNNHA and the conventional PBGT (Power BudGeT) handoff algorithms with 2 different parameters whose configurations are as follow.

PBGT-A: {TTT (Time-To-Trigger)=0ms, HOM (Handover Margin)=0dB}

PBGT-B: {TTT=256ms, HOM=6dB}

The performance of the five different algorithms is compared in the scenarios depicted in Fig.6. We assume the ST is stationary relative to the satellite with high speed v. So the relative speed of ST to satellite is v with opposite direction.

The simulation considers inter-satellite handoff rather than inter-beam handoff. Fig. 8 shows 12 coverage of 12 polar satellites designated with an ID from '1' to '12'.

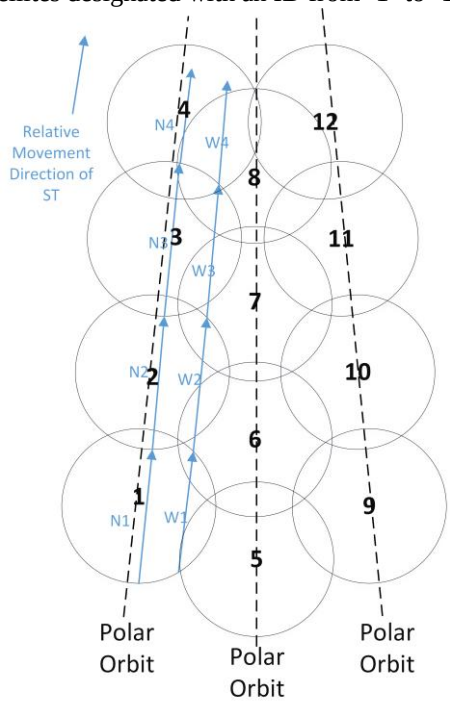
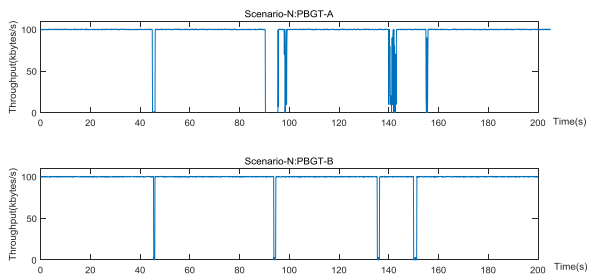


Fig. 8. Simulation scenario

1) Analysis of the scenario N



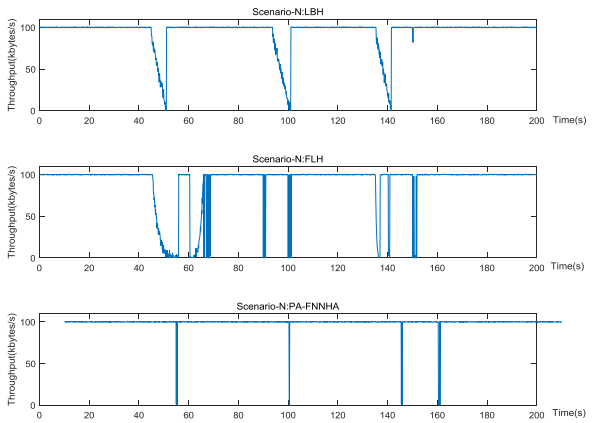


Fig. 9. Throughput performance of scenario N

As shown in Fig. 8, there are 2 simulation routes. The normal case is N1-N2-N3-N4 with moving from the good situation to the bad situation, and the worst case W1-W2-W3-W4 with moving along the edge of the coverage area. The corresponding simulation scenario to the 2 routes are marked as scenario N and scenario W respectively.

The instantaneous data throughput in Scenario N is illustrated in Fig. 9. In the graph, the curve is almost smooth in the continuous communication. When the handoff happens, the curve drops drastically because of the delays of handoffs or a redundant TTT.

The PBGT-A and PA-FNNHA result in small gap at every handoff time. On the other hand, the LBH and FLH get a big gap at some handoff time, which may leads to disconnection.

The numbers of the gaps at some time reveal the numbers of handoffs. For example, there is only a single gap at 90th second in the subgraph of the Scenario-N: PA-FNNHA, which illustrates the fast handoff at the right time. While in the subgraph of the Scenario-N: FLH, there are many gaps at about the 90th second, the 100th second, and the 150th second.

The Fig. 9 reflects the FLH is an unstable handoff algorithm. For instance, at the 65th second, handoffs take place unnecessarily, causing a waste of resource. In the FLH, the initial fuzzy logic rules and membership functions are totally defined by human, which cannot keep up with changes of environment. But the throughput performance of the PA-FNNHA indicates it adapts well in the ever-changing environment because of the training process. It shows outstanding performance in the respect of reducing ping-pong handoffs (PPHOs) and delays. The PBGT-B performs second well after the PA-FNNHA in this Scenario.

2) Simulation analysis of the scenario W

The scenario W is the worst scenario of the possible cases, as a ST moves along the route of worst signal quality. The throughput performance for Scenario W is shown in Fig. 10. The graph depicts that PPHOs occur at every handoff time under the PBGT-A setting.

The PBGT-B is a method taken by terrestrial cellular networks, which does not fit the satellite application because of the delays caused by TTT and other environment factors.

The LBH cannot always execute handoff at the correct time, resulting in many unnecessary handoffs. In addition, there exists breaking off at the 90th second to the 95th second.

The FLH behaves more poorly than that in the Scenario R, as it executes handoff unnecessarily, for instance, at the 75th second. And the FLH does not execute handoff at the necessary time, result in breaking off and connecting again, for example, at the 145th second. Nevertheless, the proposed PA-FNNHA suffers from few PPHOs handoff delays and no breaking off.

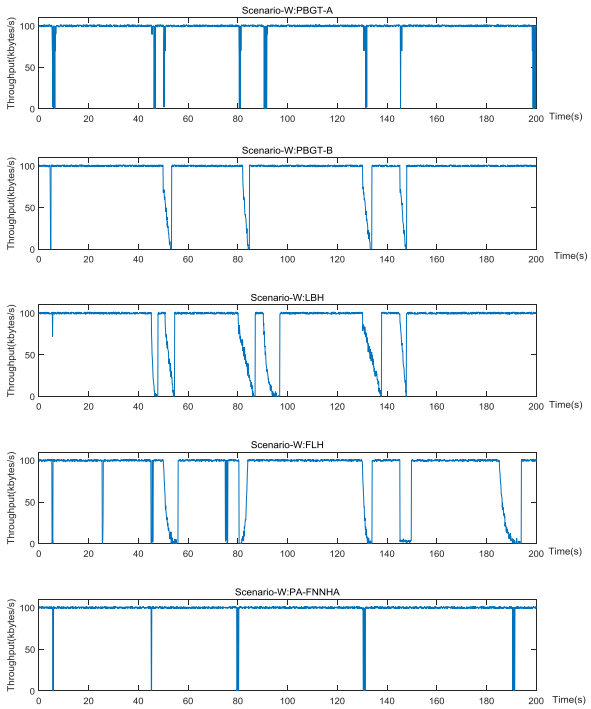


Fig. 10. Throughput performance of scenario N

B. *Overall Performance of Handoff Algorithms*

The following simulation aims to investigate the overall performance of the algorithms in terms of handoff times, blocking rate, load rate, and handoff delay. The STs of the scenario access to the network in any location and move along with a random route.

Fig. 11 indicates that the number of handoffs of the PA-FNNHA is less than that of others, which is a greater advantage. Especially with the increase of the number of user access, growth rate of number of handoffs of PA-FNNHA is significantly less than that of other algorithms. When user number reach 1000, the PBGT-A records the handoff with 3688, while the PA-FNNHA records 1612.

Input parameters of LBH, PBGT algorithm are single respectively, not taking into account the whole status of the network, leading to non-uniform network load, resulting in frequent handoff of terminals. PBGT algorithm only compare the reference signal power. The HOM of the PBGT algorithm directly affects the number of handoffs.

The LBH algorithm establishes a database of network topology to record the exact location and boundary of a coverage, and estimates the approximate service time.

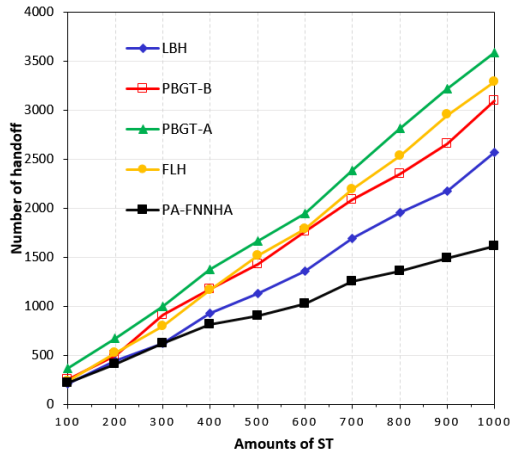


Fig. 11. Total handoff times

But this approach alone is not reliable, because the boundary of a coverage is not a perfect hexagon in the practical application which changes with the block of a moving object and other environment factors. Fewer handoffs are able to improve system utilization for handoff process requires a certain of signaling consumption.

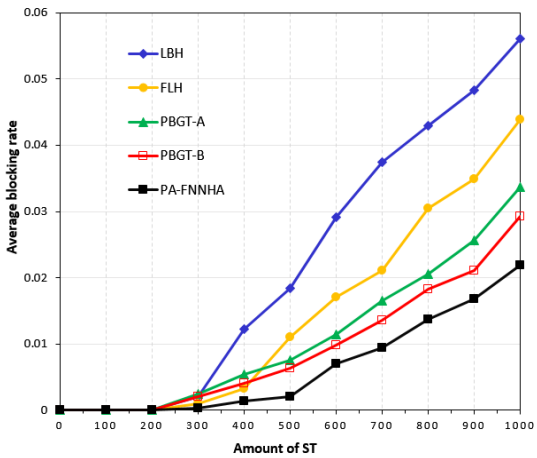


Fig. 12. Average blocking rate

The average blocking rates are shown in Fig. 12 where they increase as the number of satellite terminals grows in the simulation system. As the number of terminals is small, all blocking rates of these algorithms tend to be about 0. As the number of terminals is greater than 200, all simulation system is blocked and as terminals continue to grow, blocking ratios increase. The reason for this result is when the number of terminals within a system accumulate, subsequent terminals requesting access or handoff need enqueue. Moreover, waiting time sometimes is so long that other terminals are not able to execute enqueue. Because the PA-FNNHA estimated service time of the candidate satellite, and made a comprehensive assessment according to the load, user density, and available bandwidth which make it possible for a low block to be realized. The blocking rate of PBGT-B algorithm is also low but at the cost of frequent handoff. And the HOM and TTT have to be set correctly. The LBH method only consider location, and does not take bandwidth and whole network capacity into consideration, which easily causes mistaken handoff.

References [3] puts forward FLH, which relies on the Mamdani fuzzy logic model. It cannot adapt complex and changeable satellite environment because there is large calculating quantity and no adaptive adjustment module.

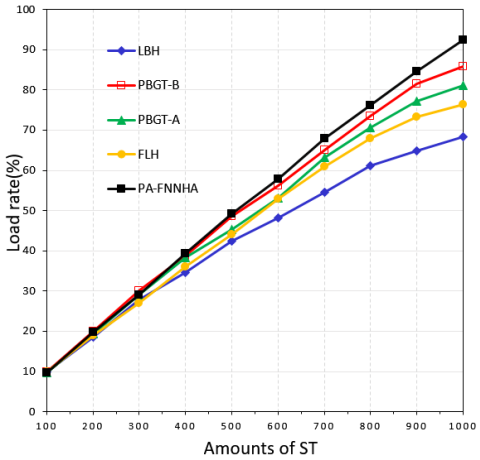


Fig. 13. Load rate

Fig. 13 presents the load rate of different algorithms under the same network. The simulation condition of the simulation network is set to be able to hold up to 1000 terminals, but due to congestion, call drop, and non-uniform load, it cannot reach its maximum number.

When the system is at full load, the load rate of the PA-FNNHA is 23.3% higher than that of the LBH, which is an obvious advantage. The PA-FNNHA takes a comprehensive evaluation of network load, user density, and other network resources, and then adjusts algorithm parameters according to different network status. Other algorithms cannot take good use of system resources, resulting in relatively low load rate.

The average handoff delay is an important indicator of performance of handoff algorithms. Average delay is consumed time in the period of the report of a ST to the success satellite handoff. And at the period, the ST gets the resources allocation. The average handoff delay is computed from total handoff delay divided by the number of STs. Handoff delay has much to do with queuing time, and consumed time of retry.

Fig. 14 shows the average handoff delay of the simulation system under the different algorithms and same network environment. In the case of the number of access terminals is small, the delay of PA-FNNHA algorithm is slightly longer than other algorithms. Because the complexity of the PA-FNNHA is higher than other algorithms. As the quantity of STs grows, blocking happens and causes handoff retry. The handoff delays of LBH, PBGT-A and FLH increase rapidly, nevertheless the delay of PA-FNNHA grows slowly, which shows that

the PA-FNNHA algorithm has certain ability for congestion control and traffic equilibrium.

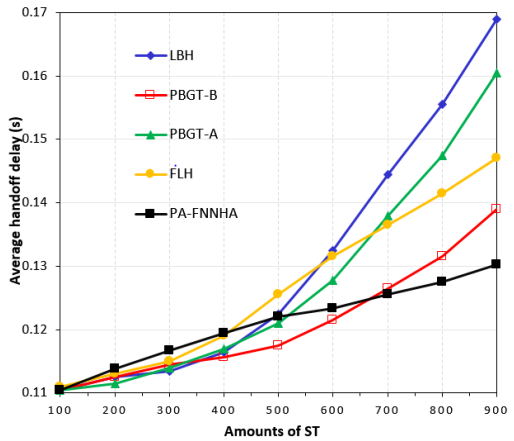


Fig. 14. Average handoff delay in the simulation system

According to the simulations and analyses, the PA-FNNHA algorithm has better performance on the aspects of total handoff times, average handoff blocking rate, load rate, and average handoff delay, which validates PA-FNNHA algorithm can realize rapid smooth handoff in mobile satellite networks.

VII. Conclusion

The PA-FNNHA handoff put forward in this paper considers the network conditions, mobile station signal and location information. It can obtain uniform load distribution, provide a fair QoS and faster response time, so that to realize smooth handoff. The multiple inputs of PA-FNNHA algorithm shows the flexibility and extension ability of the handoff framework. It can implement through a simple software and can also produce special hardware module.

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