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Multi-criteria handover management using entropy-based SAW method for SDN-based 5G small cells

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Abstract

The high data traffic requirements of the new generation 5G networks will be satisfied with effective and efficient mobility and handover management. However, dense or ultra-dense small cell (eNB) placements in 5G networks may lead to some problems, such as latency, handover failures, frequent handover, ping-pong effect, etc. In this study, we proposed an Entropy-based simple additive weighting decision-making method for multi-criteria handover in software-defined networking (SDN) based 5G small cells for the solution of the aforementioned problems. This method provides the connection of the mobile node to the most suitable eNB using bandwidth, user density and SINR parameters. The proposed handover method is compared with conventional LTE handover and distributed approach in terms of delay, block ratio, handover failure and throughput according to the varying number of mobile users. The scalability of handovers for both approaches according to the user number are also analysed. According to the simulation results, the proposed approach achieved 15%, 48% and 22% improvement in handover delay, blocking probability and throughput, respectively, compared to the conventional LTE handover.

Keywords Small cell · Handover management · 5G · SDN · Entropy-based MADM method

1 Introduction

Fifth-generation networks (5G) are expected to meet growing industrial demands both to serve more mobile nodes (MNs) and to support higher data rates [1, 2]. A large number of small cells with lower coverage are planned to meet these expectations. [3]. In this context, the communication requirements of a large number of MNs will be met through small cells. Small cells will also increase capacity, spectrum efficiency, data rate, etc. [4]. Deployment of small cells is also one of the most important solutions to increase energy efficiency in mobile communication networks. However, it also poses some problems such as interference, delay, and frequent handover. Therefore, new approaches are required to solve the problems arising with small cells.

SDN is a new paradigm for changing the way networks are designed and managed. This paradigm, that is still being developed, separates the control plane from the data plane. The control plane unit (controller) decides how to handle the network managements and the data plane devices forward traffic according to decisions made by the control plane. Simple forwarding devices in the data plane can be programmed via a well-defined Application Programming Interface (API) [5–7]. SDN is one of the most important approaches for the basic problems of small cell topologies that arise in 5G networks. The control and management algorithms of a large number of small cells with low coverage become more complex and an inextricable problem with the distributed network approach. Therefore, new innovative solutions are required for the 5G architecture with centralized SDN paradigm. The controller that has a network operating system performs the control and management operations of the entire network in the control plane, transmits the relevant rules to the data-plane elements (i.e., routers, switches, and other middleboxes) via API such as OpenFlow protocol. This centralized approach will provide important benefits for the small cell topology.

Another problem is handover management among small cells in 5G networks. The geographical area served by a

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base station (eNB) is called a small cell. eNB could serve a single small cell or use omnidirectional antennas to serve multiple small cells. However, there are no crisp boundaries for the coverage area, and overlaps occur [8]. Therefore, the MN can potentially communicate with multiple eNBs. When the MN begins to leave from a small cell, it can move to an area that overlaps with one or more small cells. When the signal from the current eNB weakens, the control of the device passes to an eNB that provides the strongest signal. The process of transferring MN to the new base station is called handover. The decision-making process for handover takes place with different parameters in a distributed way.

The decision-making process in handover management is a complex problem that could be solved by different methods. Multi-attribute decision-making (MADM) approaches are the most widely used algorithms for network selection. Simple Additive Weighting (SAW), Multiplicative Exponential Weighting (MEW), Grey Relational Analysis (GRA), Technique for Order Preference by Similarity to Ideal Solution (TOPSIS) are some of them [9, 10]. Among these ranking algorithms, SAW [11] is preferred in this study because it is simple, easy to install and has the least complexity. The ranking is generally made according to the preferences of the user in MADM algorithms. The user is always trying to maximize their benefits. However, this may lead to an inefficient performance in terms of network utilization. As a solution to this problem, we used an entropy weighting approach [12] for handover management. In the entropy method, the weight is proportional to the information. If the difference between the attribute ranges is large, it contains more information and the greater weight is assigned to this attribute. In this way, attributes that have been assigned the maximum weight are determined by an objective approach. In the entropy method, no user priority is taken into account and the weight depends on the attribute range.

In this study, a new handover management mechanism has been developed using the multi-criteria entropy-based SAW ranking algorithm running on the controller in SDN-based 5G small cell networks. The main purpose of this study is to select the most suitable eNB and assign it to mobile nodes. This handover process is performed by the controller without the need for packet exchanges between MNs and eNBs. The main contributions of the paper are as follows:

- Handover management algorithm proposed for fast and seamless connections for small cell networks.
- A new centralized, proactive, and multi-metric architecture based on SDN approach is proposed for decision-making processes in 5G small cell networks.
- A new handover management module running on the controller with entropy-based SAW algorithm has been developed for mobile nodes in the small cell networks.
- We identify several very critical metrics (i.e., bandwidth, SINR, and user density) affecting the handover management at a controller and handover management consists of the information of these metrics.
- Simulations results show Entropy-based SAW handover algorithm is superior to the conventional handover algorithm.

The rest of the paper is organized as follows. The related works are given in Sect. 2. The proposed multi-criteria handover management using an Entropy-based SAW in SDN enabled 5G small cell network is presented in Sect. 3. The evaluation scenario and the performance results are given in Sect. 4. Finally, the conclusion is given in Sect. 5.

2 Related works

There are few studies on handover management for SDN-based 5G small cells in the literature. Machine learning techniques [13–15], centralized and distributed approaches [16–19], SDN enabled handover [20, 21] have been proposed for handover management. Therefore, the multi-criteria entropy-based SAW ranking algorithm running on the controller is used for handover management in SDN-based 5G small cell architecture for the first time in the literature.

In [16], SDN-based mobility and available resource evaluation methods are proposed to solve the handover delay problem. The neighbour migration and available resource probabilities are estimated via Markov chain. As a result of the delays observed according to the densification ratio parameter, it is concluded that the proposed handover strategies are more successful than conventional LTE. The authors in [22] mentioned a general framework for the trends in mobility management taking into account some types of services (eMBB, mMTC, URLLC) emerging with the 5G. The implementation of the SDN approach is explained in 5G considering the new architectural changes implemented by Network Function Virtualization (NFV) and Multiple Access Edge Computing (MEC).

The authors in [23] emphasized the basic aspects of the handover process of small cells and identified the main problems affecting its consistency. A handover decision algorithm has been proposed for small cells to reduce the interference in the cellular uplink while extending the battery life of the user terminal. An SDN based handover architecture is proposed that has an overview of the network and can perceive its needs from all perspectives, including the physical layer, user and application level in

[24]. A context-sensitive multi-criteria handover mechanism has been developed in the SDN controller to provide differentiated services. A new combination between Software Defined Wireless Network (SDWN) and Software-Defined Transition Decision Engine (SDHDE) is proposed for optimum handover performance in the Heterogeneous Cloud Radio Access Network in [25]. In the baseband pool, a wireless controller is used to retrieve handover information from the Southbound API that communicates with end-users on the Radio Access Network (RAN). This information is transmitted to SDHDE via the controller Northbound API, and SDHDE makes the handover decision for each user in the most appropriate way.

A utility sensitive optimization algorithm is proposed for network selection in a heterogeneous environment in [10]. The weight factor has been proposed for the modified Jaya algorithm, which is calculated by analytical hierarchical process, standard deviation and entropy method. Available bandwidth, packet jitter, packet loss, cost per byte are considered for different applications such as video, audio, web browsing and e-mail transfer. The proposed algorithm is compared with multi-attribute decision-making algorithms. The authors in [18] proposed a game-theoretic approach to deal with the cell association problem by allowing the users to sense their surrounding environment and power control in the uplink of multi-service open access two-layer femtocell networks. The authors in [26] proposed an effective solution to the handover problem occurring in dense 5G networks via topology-aware handover skipping. The algorithm with different skipping techniques is compared with the conventional best-linked scheme. In [27], a new handover scheme using a collaborative cell clustering scheme has been developed to solve the handover problem in small cell users in a heterogeneous network environment, to reduce the handover overhead in the core network and also to reduce the overhead between small cells.

3 System model

In this section, SDN and 5G integration, mobility and handover operations with SDN controller, small cell deployment, and decision support system issues in the proposed architecture with all modules are explained in detail.

3.1 SDN enabled 5G small cell network architecture

It has become common to apply the principles of the SDN paradigm to communication technologies. The 4G/5G cellular network infrastructure can be strengthened with SDN principles. However, the infrastructures of access networks generally consist of special purpose, closed and proprietary devices. Converting these company-specific devices into white box counterparts that can be controlled by open-source software is one of the most important steps in terms of solving some basic problems. Cellular networks have two modules: Evolved NodeB (RAN base station, eNodeB or eNB) which provides connectivity between eNB and MNs and Enhanced Packet Core (EPC) which is responsible for mobility and control operations. These devices are produced for some special purposes. In addition, they are very problematic in terms of applying SDN principles due to their closed and proprietary nature. However, the network operators are actively following a software-defined RAN approach, as it also represents an opportunity for huge gains in the networking world [8].

SDN, which provides the separation of control and data plane functions, is convenient for handover decisions in small cells. This approach allows coordination and control of small cell clusters, radio resources, and service delivery. In the proposed architecture, control and data planes are abstracted from each other via the SDN controller. While there is a logically centralized controller in the control plane, there are small cell base stations and mobile nodes in the data plane.

The proposed SDN-based approach, given in Fig. 1, consists of control and data plane. In the proposed architecture, there is a controller which enables the programing of the small cell base stations (eNBs) by managing network resources. The controller, which is a logical central unit with an overview of the network, takes over the control and management functions and provides real-time service to MN and small cell base stations. In this way, all actual data related to small cells, handover requests of MNs and mobility management information are collected in the control plane. There are many modules related to the control plane in the controller. Our study focused on the handover management module that the most suitable small cell selection for MNs transitions between small cells is performed. Bandwidth, user density and Signal-to-interference-plus-noise ratio (SINR) parameters must be taken from both small cells and MNs in order to execute handover operations. The small cell base stations (eNB_ID) broadcast these parameters at certain times to the controller and mobile nodes (MN_ID) request handover from the controller.

Communication between the controller and data plane devices takes place via a well-defined API (such as OpenFlow protocol [28]). OpenFlow is the most widely known protocol and used for southbound API, therefore, it has been taken as a reference in our study. There are flow tables in devices on the data plane as well as the rules,

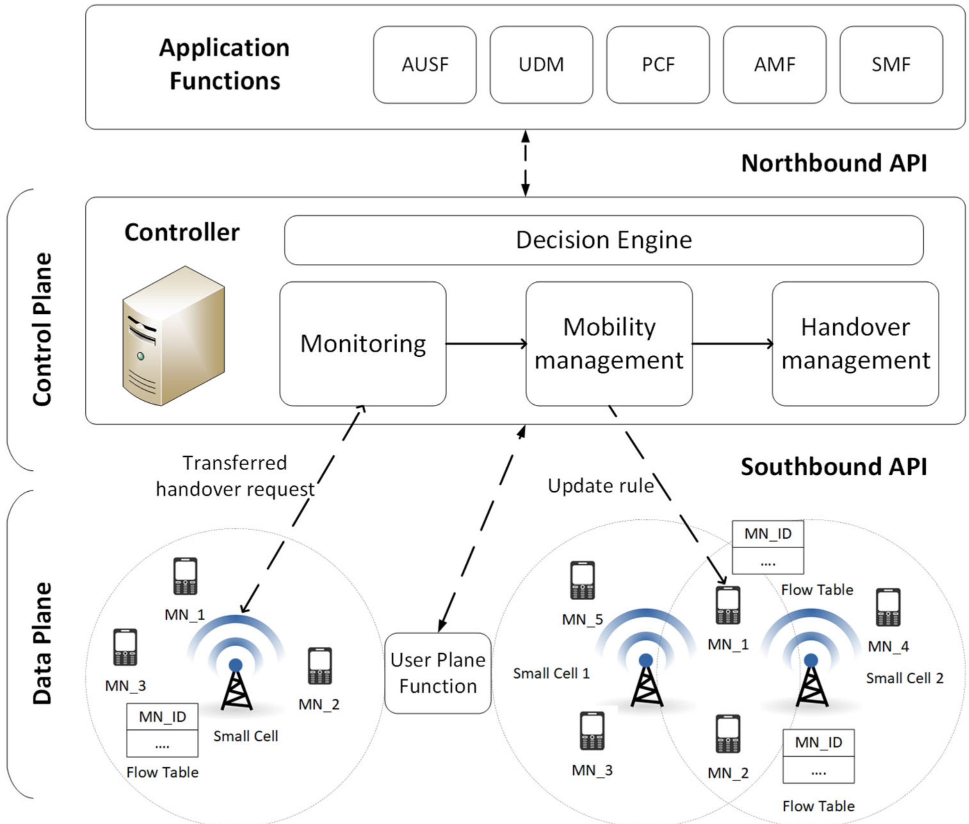

Fig. 1 The proposed network architecture

actions, and statistics fields in the flow table of OpenFlow. We have reorganized it for adaptive handover management as shown in Fig. 2. Match fields describe special handling between the controller and eNBs. The parameters related to mobile node (MN_ID) and small cell (eNB_ID) have been added to the match field for the communication from control plane to data plane. These fields are set by the controller and the decisions taken regarding the handover management are transmitted to data plane devices by updating flow tables. In this way, the MN can reach the most appropriate small cell data with the help of the controller, which has a general view of the network. In addition, the devices on the data plane execute their operations just by looking at the flow tables in case of any action. If there is no rule in the flow table, the device on the data plane communicates with the controller and requests a new flow rule.

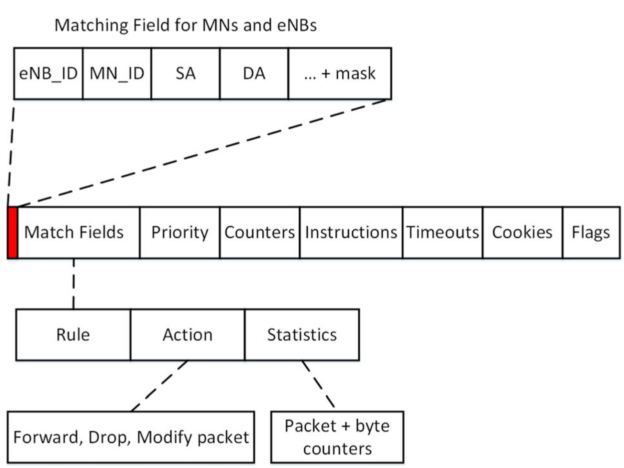

Fig. 2 Modified OpenFlow table message format

3.2 Proposed entropy-based SAW handover procedure

The flowchart of handover management proposed in the SDN enabled 5G small cell network is summarized in Fig. 3. Simple Additive Weighting (SAW) decision support system, one of the multi-criteria decision-making methods, based on the entropy weighting approach, has been used for handover management. First, the Entropy weighting method is used to calculate criterion weights, then the SAW method is used for ranking. Each eNB periodically sends relevant parameters (user density, bandwidth, SINR) to the controller. By gathering this data, the controller can access all information about the up-to-date status of the network. Thus, the controller, which has convenient information about each eNB, creates the database that will make the most appropriate handover decision

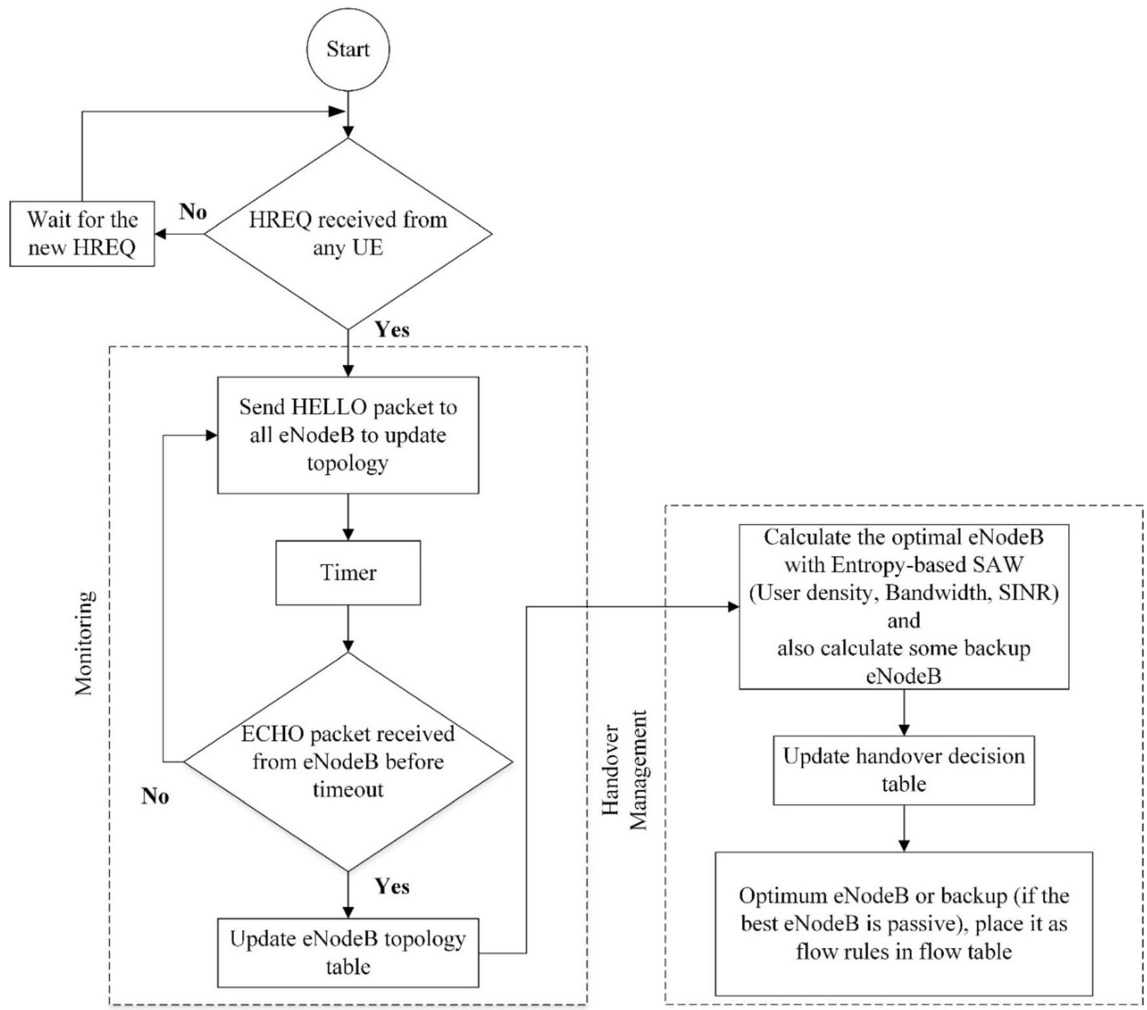

Fig. 3 Handover procedure flow diagram

for MNs. When the MN requests the most appropriate eNB data from the controller, then the proposed multi-criteria decision-making algorithm, we have created for handover management, is triggered. In light of the data obtained by the controller monitoring unit, it creates an objective weighing between the parameters and the Entropy weighting method. Subsequently, the SAW algorithm ranks all candidate eNBs. The first two eNBs (main and backup eNB_ID) with the highest performance are selected and transmitted to the MN. The result of this process is transferred to both the MN and related eNB by the controller as a flow rule in the flow table. All of these procedures are performed for all eNBs that are in the MN's trajectory.

If there is any problem with the eNB connection, the MN examines the flow rules in the flow table. The controller creates a flow rule for a backup eNB each time because of the Entropy-based SAW algorithm. The MN transmits the handover request to the next eNB (backup). If there is a flow rule for this handover request in the flow table of the new eNB, an acknowledgement (ACK) packet is forwarded to the MN. ACK indicates that the handover request has been accepted by the eNB. Thus, in case of a possible problem, communication is continued over the backup eNB. If a suitable flow rule cannot be found in the flow table of MN and eNB, this request is transmitted to the controller as shown in Fig. 3. The controller repeats the steps to create new flow rules and update the flow tables of the relevant nodes (MN or eNB). The Entropy-based SAW used in the handover management of the controller is explained in detail in Sects. 3.2.1 and 3.2.2.

3.2.1 Entropy weighting method

One of the most prominent approaches in social science, engineering, physics, and information theory is Entropy. The entropy weighting method developed by Shannon is based on the variation degree of a certain index used in weight calculation. Here, the low information entropy provides an increase in the degree of variation, so the larger weight should be assigned to that. The reason for increasing the weighting can be expressed as more information content. Conversely, when it contains less information, a large entropy value indicates small variation. Therefore, it causes smaller weighting. The main issue of the entropy method is that the information comes from the oppositeness between data sets. Objective weights of qualities are determined as to how separate or differentiated the outputs of alternatives according to each attribute, i.e. "the intensity of their opposition". This method comprises a few steps of object gathering, normalization, determination of weight, and calculation of synthetic index. The steps used for weight calculation are as follows:

Step 1: Creating the decision matrix: The decision matrix is created with addressing the network and related features.

Step 2: Normalization: It is calculated for each parameter as given in Eq. 1.

$$N_{ac} = \frac{B_{ac}}{\sum_{a=1}^{x} B_{ac}} \tag{1}$$

Step 3: Calculating entropy: First, the entropy coefficient according to Eq. 2 is found. Here, the entropy coefficient (y) is the logarithmic state of the number of base stations considered. Subsequently, the entropy value for each criterion is calculated according to Eq. 3. It is summed by multiplying the normalized values with the logarithmic values of these values. This total is multiplied by the last 'y' entropy coefficient and placed in the related field.

$$f = \left(\ln(y)^{-1}\right) \tag{2}$$

$$e_c = -f\sum_{c=1}^{y} N_{ac} lnN_{ac} \tag{3}$$

Step 4: Weighting calculation: The weight value of each criterion is obtained according to Eq. 4. w_c is the degree of importance of criteria c.

$$\sum_{1}^{x} w_c = 1 \quad w_c = \frac{1 - e_c}{\sum_{1}^{x}(1 - e_c)} \tag{4}$$

The symbols used in these equations are; a is alternate, c is criteria, N_{ac} is normalized values, B_{ac} is benefit values, f is entropy factor, e_c is entropy value, w_c is weighted value. In this study, the entropy-weighting model is used for finding the appropriate weight for each criterion. The method is based on objective criteria that will enable the solution to be searched in the system rather than the user preference. In this way, errors due to user preferences are prevented.

3.2.2 Simple additive weighting (SAW) method

Multi-attribute decision-making (MADM) algorithms are one of the most widely used approaches for network selection. SAW is an MADM method that is the simplest and most widely used algorithm. The performance value of an alternative is calculated as the weighted sum of the attribute degree. There are two different criteria in SAW method, namely, benefit and cost. In the SAW method, when calculating the benefit criterion, the value that each alternative receives in terms of each criterion is divided by the maximum value. When calculating the cost criterion, the minimum value is divided into each value from the values that each alternative receives in terms of each criterion. Then the obtained results are multiplied by the criterion weight and the alternative preference value is calculated. The steps used in the SAW algorithm are:

Step 1 Normalization of decision matrix is calculated according to Eq. 5. In the first step in SAW method, the decision matrix consisting of m alternatives and n evaluation criteria is normalized with the help of the following equation.

$$r_{ij} = \begin{Bmatrix} \frac{x_{ij}}{\max x_{ij}} i = 1,\ldots,m; j = 1,\ldots,n \, benefit \, criteria \\ \frac{\min x_{ij}}{x_{ij}} i = 1,\ldots,m; j = 1,\ldots,n \, cost \, criteria \end{Bmatrix} \tag{5}$$

Step 2 Normally, the criterion weights of the SAW method are calculated using Eq. 6. However, entropy-weighting equations are used to obtain more realistic results in this study.

$$w = \frac{C1}{C1 + \ldots + Cn} \times 100\% \tag{6}$$

Step 3 The preference values of the alternatives and the total preference values of each alternative are calculated with the help of Eq. 7.

$$V_i = \sum_{j=1}^{n} w_j r_{ij} i = 1,\ldots,m \tag{7}$$

3.3 Algorithm complexity

An algorithm is a structure consisting of a finite number of tasks to solve a specific problem in a given time frame. Algorithms have some advantages and disadvantages. The process of examining the behaviour of algorithms before coding is called complexity analysis [29]. These analyses are calculated according to the input parameters and iteration numbers in the algorithm. The complexity of a system *(S)* is the number of resources required (used) for a process *P* that includes *S*. The steps used for ranking in most MADM algorithms are basically similar. Complexity analyzes of AHP [30], TOPSIS [31], GRA [32] and other MADM algorithms are calculated according to the number of mutual comparisons of the alternatives. New alternatives cause additional calculations as they have to be compared with existing alternatives and are expected to change the existing ranking as well. For example, the complexity analysis for the worst case scenario of TOPSIS has been determined as $O(n^2)$ [33, 34]. When the equations given in Sect. 3.2.2 are examined, it is seen that the complexity analysis result is O(n) since the SAW method does not have an additional cyclic operation for weighting. The differences other than generalizations made for MADM algorithms are due to the execution time, which gives the number of operations that are considered basic, to be executed, and the input parameters that vary according to the scenarios used.

In our study, the SAW algorithm is used with entropy weighting approach and utilized for handover management in SDN-based 5G small cell networks. The centralization of the control plane is an important limiting factor for the computational complexity of handover management. Therefore, a new efficient handover algorithm has been proposed, focusing on a simple model that can provide services for more MNs and small cells. Based on the SDN approach, this method aims to reduce computational complexity. This goal is achieved thanks to a centralized SDN controller that collects data and makes decisions, rather than distributed handover decision making. Thus, the computational complexity of the Entropy based SAW algorithm has been reduced and also the additional memory resources allocated for storing the data before making a decision are made flexible. The complexity analysis of the proposed algorithm is calculated as O (i•s•m) depending on the number of MNs (m), eNBs (s) and iterations (i).

4 Performance evaluation

The performance analysis of the proposed approach is carried out in the Riverbed Modeler (OPNET) simulation software. First, the study results of the Entropy-based SAW MADM algorithm in a sample network scenario are analyzed gradually. Then, handover delay, blocking probability, failure, and throughput results of the conventional LTE and proposed approach for different numbers of MNs are examined.

4.1 Entropy-based SAW: a numerical example

In an example network scenario, four different small cell base stations (eNBs) are taken into consideration and the entropy method is used in weighting the criteria to be used for the performance of these base stations. As stated in the algorithm complexity analysis, the execution time value of the proposed algorithm is proportional to the eNB, MN and number of iterations. In this context, as the number of devices in the environment increases, the execution time value is expected to increase. First, the values taken from the base stations for the formation of the decision matrix are given in Table 1. The normalized standard decision matrix with the help of Eq. 1 is created as given in Table 2.

Entropy value for each criteria is calculated as given in Table 3 with the help of Eqs. 2 and 3. It is summed by multiplying the normalized values with the logarithmic values of these values. The total is multiplied by the entropy coefficient. The entropy coefficient is the logarithmic state of the number of base stations.

The weight value of each criterion is calculated with the help of Eq. 4. Each of the entropy values is subtracted from 1 to calculate the weight values. The entropy value of the desired criterion is subtracted from 1, and the weight value is found by dividing the first calculated sum. These values are given in Table 4. The weights obtained from the entropy method should be between zero and one, and the sum of the obtained weights should give a value of one.

Table 1 Decision matrix

Alternate	Criteria		
	Bandwidth (MHz)	SINR (dBm)	User density (%)
eNB1	600	20	20
eNB2	800	3	50
eNB3	500	15	30
eNB4	1500	10	10

Table 2 Normalized decision matrix

Alternate	Criteria		
	Bandwidth	SINR	User density
eNB1	0.176470588	0.416666667	0.181818181
eNB2	0.235294117	0.0625	0.454545454
eNB3	0.147058824	0.3125	0.272727272
eNB4	0.441176471	0.208333333	0.090909090

Table 3 Calculated entropy values

Bandwidth	SINR	User density
0.930161209	0.886063654	0.894964536

Table 4 Calculation of weight values

Bandwidth	SINR	User density	Sum
0.241815194	0.394501955	0.363682851	1

According to the entropy results, it is seen that the most important criterion is the SINR, the least important is the Bandwidth. These weights will be used in the SAW method.

The entropy weighting method calculates the weighting of each attribute of small cell base stations. The calculation is performed with objective criteria and will be used to evaluate the performance of base stations. The second stage is the application of the SAW method. In the SAW method, the decision matrix is formed as in Table 5. As shown in Eq. 5, each value must be divided by the maximum or minimum value in its row in order to normalize the decision matrix. The values obtained from the result are given in Table 6.

The normalized values are multiplied by the weight values calculated according to the Entropy weighting method and the utility matrix of the SAW method will be formed. Table 7 shows the utility matrix calculated by SAW method.

As a result, all the values are summed up in columns and the highest value gives the best result. The ranking resulting from this calculation is given in Table 8. As can be seen, eNB4 small cell base station has the highest result compared to other base stations. eNB1, eNB3 and eNB2 base stations, respectively, have the values of 0.673069458, 0.497709148, and 0.260879967.

Table 6 Decision matrix normalized to SAW method

Criteria	Alternate			
	eNB1	eNB2	eNB3	eNB4
Bandwidth	0.4	0.533	0.333	1
SINR	1	0.15	0.75	0.5
User density	0.5	0.2	0.333	1

4.2 Simulation results

The simulation results obtained from the Riverbed Modeler are given in this section. An example simulation scenario is given in Fig. 4. In our simulations, handover delay is first considered and compared to conventional handover scheme (LTE) with respect to different number of MNs. In addition, handover blocking probability, failure ratio and throughput results are also examined according to different numbers of MNs. In our study, IEEE 802.11 (CSMA/CA) medium access control protocol has been used between MN, controller and eNBs. In this protocol, all nodes sense the communication medium, if it is idle, they send their packets to the destination. If not, it waits for a random period (bakoff time). Another important detail in our study is defining a special priority for control packets which are used between controller and data plane nodes. The purpose of this priority is to minimize the delay of control packets that may occur due to the SDN approach. This priority was achieved by configuring the number of contention windows (CW). The parameters used in the simulation are given in Table 9.

Riverbed Modeler [35] is a powerful network simulator. Performance, availability and optimization cost are among the most important goals to using it. Riverbed Modeler offers various tools for designing, simulating the model, data mining and various analyses by considering different alternatives. In this simulation software, a wide variety of interconnected networks can be simulated. The models have a hierarchical structure. The behaviour of a protocol is programmed in a state diagram with the Proto-C programming language. In the middle tier, various functions

Table 5 Decision matrix for SAW method

Criteria	Alternate					
	Types of criteria	eNB1	eNB2	eNB3	eNB4	MAX-MIN
Bandwidth	Max	600	800	500	1500	1500
SINR	Max	20	3	15	10	20
User Density	Min	20	50	30	10	10

Table 7 Utility matrix

Criteria	Alternate			
	eNB1	eNB2	eNB3	eNB4
Bandwidth	0.096726078	0.128968104	0.080605065	0.241815194
SINR	0.394501955	0.059175293	0.295876466	0.197250978
User density	0.181841425	0.072736570	0.121227617	0.363682851
Sum	0.673069458	0.260879967	0.497709148	0.802749022

Table 8 Entropy-based SAW ranking results

Base stations	Results	Ranking
eNB4	0.802749022	1
eNB 1	0.673069458	2
eNB 3	0.497709148	3
eNB 2	0.260879967	4

such as transmitting and receiving packets, buffering and forwarding are performed by each of the separate objects.

Handover delays of proposed and conventional handover approaches according to different number of MNs are evaluated in order to show the effects of MN number on handover delay. MN and small cell numbers are two factors that affect the density of the environment. While increasing the number of MNs in our simulation, we evaluate the

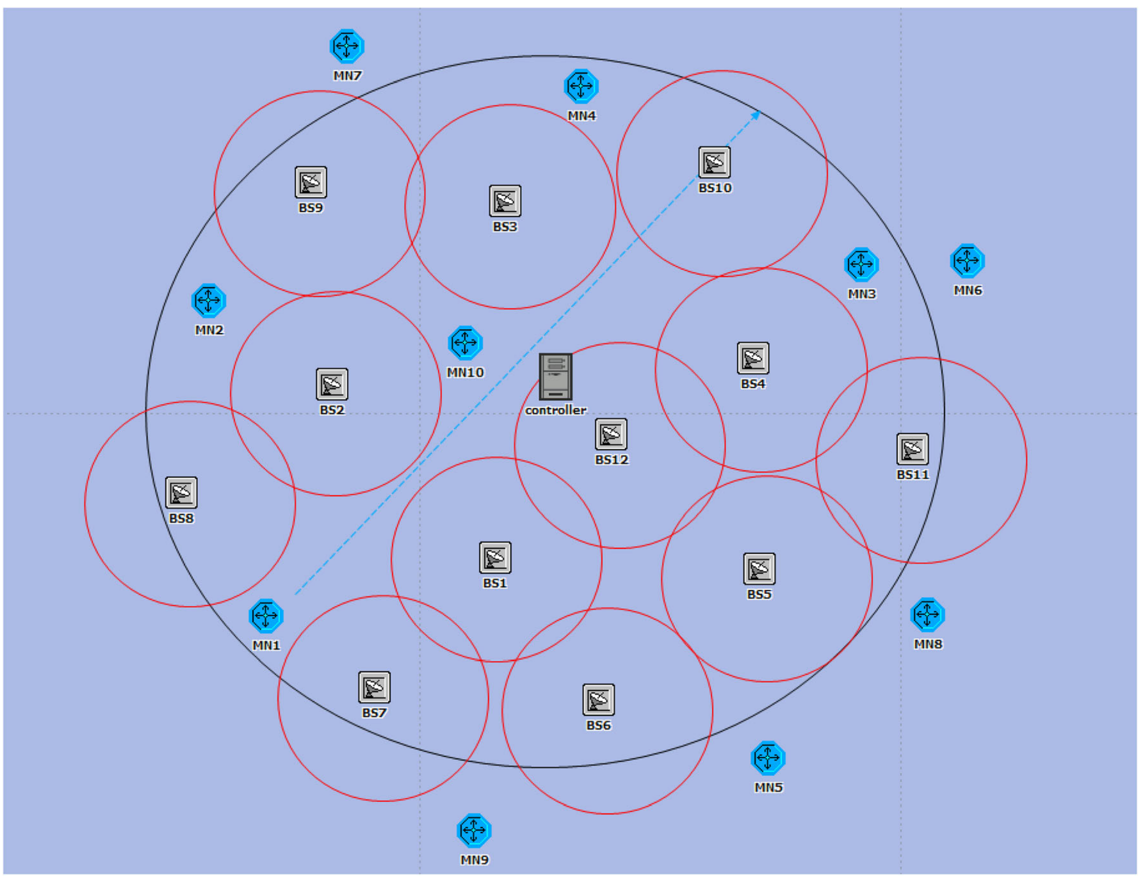

Fig. 4 An example simulation scenario in the Riverbed Modeler

Table 9 Simulation parameters

Parameter	Value
Simulation time	3600 s
Number of small cells	5–10
Radius of small cells	200 m
Number of mobile nodes	10–80
Mobile nodes distribution	Randomly
Small cell communication protocol	IEEE 802.11 (CSMA-CA)
Priorities	Control packets CW = 32 Normal packets CW = 16
Bandwidth	10 MHz
BS status transmission period	100ms
Tx power for small cells	30 dBm
Antenna height for small cell	10 m
Carrier frequency for small cell	3.5 GHz
Mobil node speed	5–15 km/h

success of the proposed algorithm by keeping the small cell number constant. Considering the conventional handover mechanism in the same scenario, as the number of mobile nodes increases, the queue and handover delay increase. In the proposed approach, while the flow rule increases, the number of handovers increases. However, the handover delay is less than the conventional handover mechanism as can be seen in Fig. 5. The handover delay of the proposed approach is approximately 15% lower than the conventional handover mechanism. The main reason for this result is that the most accurate eNB decision is made thanks to the MADM algorithm running on the controller.

In order to show the effects of MN number on handover blocking probability, the blocking probability of the proposed and conventional handover approaches are evaluated according to different MN number. Blocking probability, one of the main quality of service (QoS) parameters, refers to the possibility of rejecting a new handover request due to lack of resources. Blocking probability is directly related to density in neighbouring small cells and mobility of MNs. In this context, both the increase in the number of MNs and mobility in the environment are some of the crucial problems that increase the blocking probability in the handover process. As a solution to this problem, it is seen that a controller has a general view of the network, and an intelligent algorithm working on this unit is needed. Due to this need, a new handover management algorithm working on the controller has been developed. This algorithm performs a ranking by taking real-time status information of eNBs and makes the most appropriate handover decisions. These decisions are transmitted to the relevant MN and eNBs as a flow rule. Thus, as seen in Fig. 6, it has been observed that there is a decrease in blocking probability values compared to the conventional approach. It is seen that the proposed approach is approximately 48% lower than the conventional handover mechanism in terms of handover blocking probability.

The throughput of proposed and conventional handover approaches according to different number of MNs are examined in order to show the effects of MN number on throughput. As seen in Fig. 7, the throughput of the proposed handover algorithm is higher than the conventional approach. The main reason for this result, a centralized SDN controller performs the coordination task among small cells quickly and efficiently. In the conventional approach, the increasing number of MNs causes more

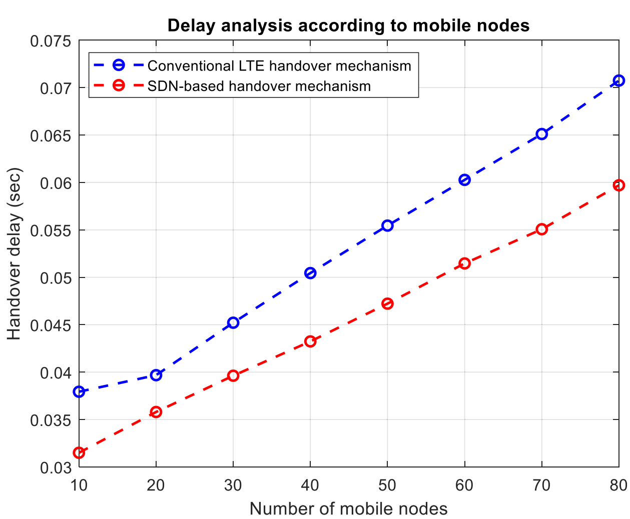

Fig. 5 Delay analysis according to mobile nodes

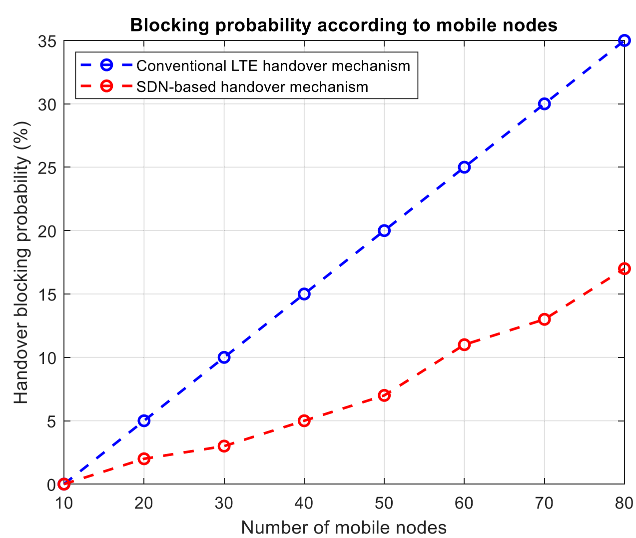

Fig. 6 Blocking probability according to mobile nodes

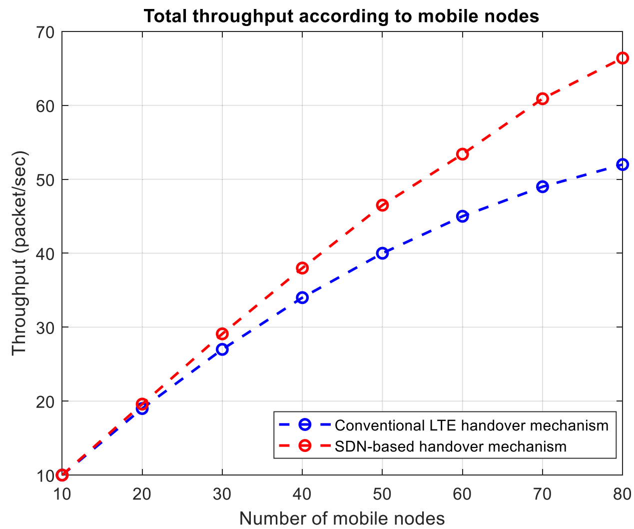

Fig. 7 Total throughput according to mobile nodes

handover among small cells. The lack of a centralized SDN controller causes wrong decisions or frequent handover (causes the ping-pong effect), so throughput decreases. As a result, transferring handover decision functions from the data plane to the control plane enables the solution of the above-mentioned problems and increases the performance of the network.

When the number of MN in the topology increases, the variation of handover failure ratio according to both distributed and centralized approach is given in Fig. 8. According to the obtained results, it is seen that the centralized approach significantly reduces the handover failure ratio. The conventional handover mechanism is maintained with a distributed approach. However, SDN is a centralized approach that allows 5G small cell base stations and MNs to be managed via a control software (running on the controller). This approach, which enables the abstraction of the control and data planes, is to centrally collect the handover parameters (bandwidth, SINR, and user density), make an optimal decision (with Entropy-based SAW algorithm), and send them to the nodes (eNBs and MNs) to execute the relevant control parameters (flow rules). In this way, the handover failure ratio is reduced by optimal decisions.

In addition, the delay results of scenarios with different user densities have been compared according to conventional and proposed architecture and discussed in terms of scalability. As seen in Fig. 9, delay increases as the number of MN in the environment increases in both approaches. However, this increase is a lower level in the proposed approach. There is still no common standard developed for dynamic network management in conventional network infrastructures. Therefore, as the network traffic or the number of flows in the network increases, there is no mechanism with a general view that can keep the QoS requirements at an acceptable level. These conditions cause a rapid decrease in performance after a certain scalability level. The separation of data planes with the centralized SDN controller and the controller's ability to manage all nodes is an effective solution to the scalability problem. It is very important for the controller to have the general view of the network, to detect the flow load of small cells and to manage handover requests of MNs in dynamic network conditions more fairly in terms of increasing scalability performance. In addition, increasing scalability in this architecture is proportional to the capacity of a controller that can manage more flows.

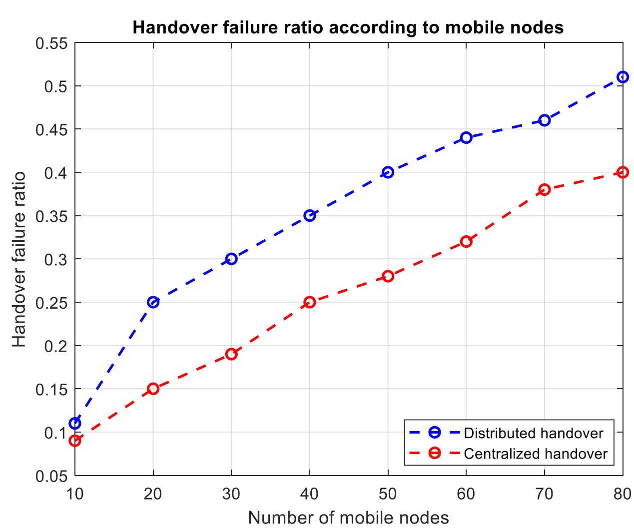

Fig. 8 Handover failure ratio according to number of mobile nodes

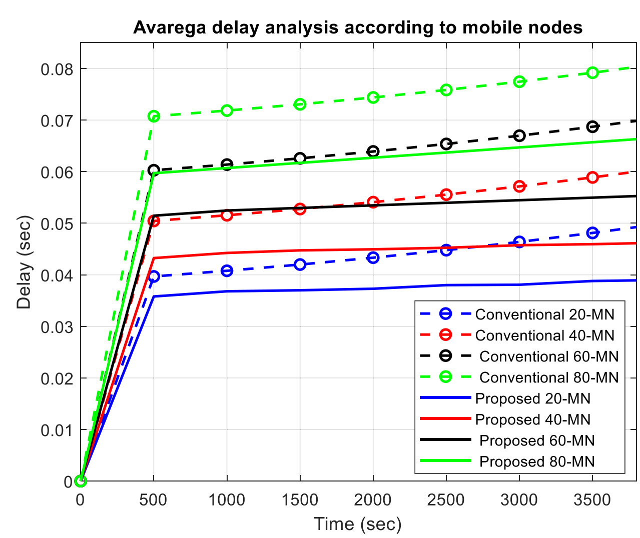

Fig. 9 Average delay analysis according to mobile nodes

In the proposed architecture, the controller performs the handover process by getting each flow from mobile nodes periodically according to the flow load of the eNBs that receive information. For this reason, as shown in Fig. 9, the controller increases the scalability of the system with dynamic flow management by keeping each flow at a certain level. However, in the conventional approach, this process is performed statically, without considering the workloads of eNBs. Although the proposed architecture seems to perform better, it also has some disadvantages. The major disadvantage of the SDN approach is that the centralized controller means a single point of failure. Although this is not the subject of our study, it is still among the problems seeking solutions.

5 Conclusions

One of the main issues for wireless 5G networks is how to optimally meet the QoS requirements of mobile nodes with an increasing number of small cells. In this study, a handover management strategy with multi-criteria entropy-based SAW decision-making method is proposed for SDN based 5G small cell networks. The proposed algorithm selects the most suitable small cell according to bandwidth, SINR, and user density parameters and assigns them to the relevant mobile nodes and small cell via flow rules. The centralized SDN controller carries out all decisions with ensuring the abstraction of control and data planes from each other. The nodes (mobile nodes and eNBs) in the data plane have been transformed into simple forwarding devices and only process the flow rules in the flow tables. According to the simulation results, it has been observed that the proposed approach achieved 15%, 48 and 22% improvement in handover delay, blocking probability and throughput, respectively, when the number of mobile nodes increased compared to the conventional LTE handover mechanism. In future studies, artificial intelligence, machine learning techniques are planned to select the most suitable small cell for ultra-dense and heterogeneous networks.

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