IEEE Access
Multidisciplinary | Rapid Review | Open Access Journal

Received December 28, 2017, accepted February 15, 2018, date of publication March 12, 2018, date of current version April 18, 2018.

Digital Object Identifier 10.1109/ACCESS.2018.2811047

Adaptive Hysteresis Margin Based on Fuzzy Logic for Handover in Mobile Networks With Dense Small Cells

KETYLLEN DA COSTA SILVA[1,2], ZDENEK BECVAR[2], (Senior Member, IEEE), AND CARLOS RENATO LISBOA FRANCES[1]

[1]Post -Graduation Program in Electrical Engineering, Federal University of Pará, Belém 66075110, Brazil
[2]Department of Telecommunication Engineering, Czech Technical University in Prague, 166 27 Prague, Czech Republic

Corresponding author: Zdenek Becvar (zdenek.becvar@fel.cvut.cz)

This work was supported in part by the Coordination for the Improvement of Higher Education Personnel-CAPES/Pro-Amazônia and National Council for Scientific and Technological Development–CNPq and in part by the Czech Technical University in Prague, under Grant SGS17/184/OHK3/3T/13.

ABSTRACT To satisfy requirements on future mobile network, a large number of small cells should be deployed. In such scenario, mobility management becomes a critical issue in order to ensure seamless connectivity with a reasonable overhead. In this paper, we propose a fuzzy logic-based scheme exploiting a user velocity and a radio channel quality to adapt a hysteresis margin for handover decision in a self-optimizing manner. The objective of the proposed algorithm is to reduce a number of redundant handovers and a handover failure ratio while allowing the users to exploit benefits of the dense small cell deployment. Simulation results show that our proposed algorithm efficiently suppresses ping pong effect and keeps it at a negligible level (below 1%) in all investigated scenarios. Moreover, the handover failure ratio and the total number of handovers are notably reduced with respect to existing algorithms, especially in scenario with high number of small cells. In addition, the proposed scheme keeps the time spent by the users connected to the small cells at a similar level as the competitive algorithms. Thus, the benefits of the dense small cell deployment for the users are preserved.

INDEX TERMS Handover, hysteresis margin, mobile networks, small cells, fuzzy logic, self-optimization.

I. INTRODUCTION

As demands on mobile traffic are increasing exponentially due to new mobile devices, services, and applications, mobile networks should be prepared for a mobile traffic growth over the next decade. A powerful technique to address the mobile traffic growth is a network densification, i.e., provisioning of more base stations to serve a geographical area. With network densification, the system throughput can be enhanced exploiting spatial reuse of the spectrum as the access network is brought closer to the user [1]. The network densification is implemented through a massive deployment of small cell base stations (SCeNBs), i.e., base stations with a small coverage due to a low transmission power. The 5G networks are expected to deal with many SCeNBs deployed dynamically and heterogeneously across the network.

In the mobile networks, continuous connection during a user's movement is ensured by handover of a User Equipment (UE) between two base stations (denoted as eNB). The handover process is a core element of the mobile networks in terms of a support of the user's mobility. The handover also impacts on the overall network performance as shown, e.g., in [2] or [3]. One of the challenges in mobile networks concerns the need to offer the best possible experience with an infinite number of rapidly proliferating devices. An increase in both size and complexity of the current mobile networks leads to a more complex network management. The recent deployment of the SCeNBs in order to provide higher capacity brings a significant increase in the number of network elements, making configuration and maintenance of the network more complicated. In this case, a classic manual and field trial-based approaches for network planning and management may lead to suboptimal solutions even in case of a minor change of the environment [4]. In the light of this, it is necessary to assess the effects of the growing number of the SCeNBs deployed in the network in terms of mobility management.

Technical challenges, which must be solved to fully exploit the dense SCeNB deployment are described, e.g., in [5]–[8]. Regarding the mobility management, one of the main problems is to find a compromise between an elimination of redundant handovers caused by the dense deployment of SCeNBs and a high utilization of the available communication resources of the SCeNBs [9].

Several schemes addressing mobility management are described in, e.g., [10] and [11] where the authors investigate the impact of various parameters on the handover and propose an adaptive adjustment of these parameters, respectively. Furthermore, in [12], Kuang *et al.* combine an inter-cell interference coordination (ICIC) techniques with the handover process to allow an efficient reduction of interference. Nevertheless, it has negative impact on the ping pong rate mainly in scenarios with high speed UEs. In [2], interference-aware and energy-efficient handover decisions exploiting two handover hysteresis margins is proposed to mitigate redundant handovers. All the schemes in [2], [5]–[12] are able to improve specific handover performance metrics, but it is at the cost of a worsening other handover metric(s).

Another option for handover decision optimization is based on fuzzy logic. In [13], the fuzzy logic is considered for an optimization of the handover decision parameters. The paper shows promising performance of the fuzzy logic based solutions for the handover optimization in a general macro cell scenario. The fuzzy logic is then exploited also in [14] where fuzzy rules and membership functions are adapted according to previous handovers. Based on these two papers, in [15], we outline and evaluate a self-tuning handover algorithm (STHA) to diminish the ping pong effect and a handover failure ratio (i.e., the ratio of handovers not completed successfully) exploiting knowledge of the UE's velocity and the radio channel quality combined into a fuzzy-logic system that represents an additional step in the handover decision algorithm. In the STHA [15], first, the conventional handover condition should be fulfilled. Then, the level of signal from the serving eNB is compared with the fuzzy-based generated threshold for handover initiation

In this paper, we take advantage of findings from our former work presented in [15] and we modify and extend the STHA it in the following directions:

- First, the fuzzy logic is integrated to the conventional handover decision via a dynamically adjusted hysteresis margin. This means both signal level from the serving and target eNBs are put into the context of a dynamically adjusted hysteresis margin, which is an output of a fuzzy logic based system.
- Second, we propose a new fuzzy inference scheme tailored for the handover optimization purposes and suitable for the proposed handover decision algorithm. This new inference scheme derives the hysteresis margin dynamically according to the actual UE's velocity and the radio channel quality.
- Third, we demonstrate superior performance of the proposed handover decision scheme with respect to state of the art handover decision algorithms (incl. our prior work [15]) and we show that the ping pong effect can be almost eliminated by the proposed algorithm. We investigate the performance for various numbers of the SCeNBs to confirm robustness of the proposed algorithm. We also confirm that the time spent by the UEs connected to the SCeNB is kept at a similar level as for the competitive algorithms guaranteeing that the benefits of the dense SCeNB deployment are preserved.
- Fourth, in order to better understand the main sources of the performance gain, we evaluate an impact of the inputs of the proposed fuzzy logic system on the performance of the proposed algorithm.

The rest of the paper is organized as follows. Next section presents an overview of related works in the context of handover optimization. In section III, the fuzzy logic scheme is outlined and our proposal is described in details. Then, in section IV, the simulation models and scenarios are specified. The simulation results are presented and discussed in Section V. Finally, the last section summarizes the major conclusions and outlines potential future research directions.

II. RELATED WORKS

This section provides thorough overview of the work related to optimization of the handover procedure in the mobile networks.

The main challenges related to handover procedure are studied in [3]. The authors discuss the handover decision algorithms and provide a comparison of existing algorithms. The paper points out that the optimization of the handover decision parameters is the most prominent challenge. The authors conclude the values of the handover decision parameters should be changed dynamically and should be adapted in line with the UEs preferences. The handover decision based on an adaptation of the handover decision parameters is discussed, e.g., [16]–[18].

In [16], Becvar and Mach present a novel handover procedure based on an estimation of the UE's throughput gain. The gain in throughput is derived from the estimated evolution of the signals levels of all involved cells and from an estimated time spent by the UEs in femtocells. The handover is initiated only if the estimated gain in UE's throughput exceeds a predefined threshold. The results show high efficiency of the proposed decision in mitigation of redundant handovers. However, the proposed idea is only limited to cells with a very small radius where the estimation is accurate enough and cannot be applied to general small cells.

A self-optimization scheme that adjusts the handover parameters to minimize Radio Link Failures (RLFs) for dynamic small cell networks is presented in [17]. The scheme first detects the types of RLF and then adjusts the handover parameters accordingly. Simulation results show that the scheme can eliminate RLF. Nevertheless, the convergence time of the algorithm is high, and the analysis of the ping pong effect is neglected. Another approach with aim to mitigate mobility problems is showed in [18] where a data-driven handover optimization approach is proposed. The authors evaluate five types of handovers: too-late handover, too-early handover, handover to wrong cell, ping pong handover and unnecessary handover. The proposed approach collects data from the signal level measurements and provides a model to estimate the relationship between the Key Performance Indicators (KPI), represented by a weighted average of the five different mobility problem ratios, and features from the collected dataset. Based on the model, the handover parameters, including the Hysteresis Margin and time-to-trigger (TTT), are optimized to minimize the KPI. Simulation show that the proposed approach could effectively mitigate mobility problems. However, the neural network considered to estimate the KPI function requires a large diversity of training for real-world operation, which is a notable constraint for the mobile networks with dense SCeNBs operating in a self-optimizing manner.

Lee *et al.* [19] propose a cost-based adaptive handover hysteresis scheme that focuses on a performance improvement in terms of the handover failure ratio in real time. The cost function for vertical handover in heterogeneous network is provided as a weighted sum of normalized functions by following dominant factors: a load difference between the target and serving eNBs, UE's velocity, and the service type. The simulation results show a lower handover failure ratio than the compared schemes, but other important handover performance indicators, such as the number of handovers or ping pong ratio are not considered.

Besides hysteresis margin, also other parameters can be considered for adjustment of the handover procedure. In [10], an impact of various offsets and timers on the efficiency of the handover in heterogeneous networks is investigated. The analysis shows that large and positive offset values, which are typical for macro-only deployments, lead to a higher number of handover failures in heterogeneous networks. On the other hand, small and negative offset values result in a more frequent ping pong (i.e., repeated non-beneficial handovers performed between two eNBs). In [12], an impact of three handover-related parameters, i.e., time-to-trigger, hysteresis margin, and Reference Signal Received Power (RSRP), is analyzed in terms of the handover failure ratio and the ping pong ratio in an environment close to a real world. The authors also investigate an impact of cell range expansion (CRE) and ICIC techniques on the mobility support efficiency. The paper reveal that the impact of CRE and ICIC depends on the handover type (i.e., macro-to-pico, pico-to-macro, pico-to-pico and macro-to-macro). The authors further propose a dynamic ICIC mechanism assisting the handover process. The proposed combination of handover with ICIC allows an efficient reduction of interference. Nevertheless, it increases the ping pong ratio mainly in high speed scenarios.

In [20], Fischione *et al.* propose a Generalized Extended Last Squares Handover (GELS) to select and optimize the hysteresis margin. This work is further enhanced by a new modeling of the handover process taking into account a general handover mechanism in [21]. The proposed system allows dynamic optimization considering the probability of outage and the probability of handover. The results shown that the GELS outperforms existing handovers. However, the gain is obtained at the cost of high complexity.

The paper [22] proposes a self-optimizing handover hysteresis scheme with dual mobile relay nodes for wireless networks in high-speed mobile environments. The proposed mechanism adapts the hysteresis margin and cell individual offset based on the velocity of the vehicle and the handover performance indicator of the cell characterized as a summation of the handover failures, handover ping pong ratio, and RLF indicators. The results show superior performance with respect to the conventional schemes and confirms that the fixed parameter setting is adequate for common scenarios. However, in a high-speed environment, a more flexible scheme is necessary. In [23], Xenakis *et al.* target to optimize the handover by employing interference-aware and energy-efficient handover decisions exploiting two handover hysteresis margins. The first hysteresis margin is considered to avoid cells that can compromise service continuity, e.g., due to poor channel conditions. The second hysteresis margin identifies the cell with the minimum requirements in terms of RSRP. The simulation results indicate that the proposed algorithm allows to double the macrocell offloading ratio, enhance the uplink capacity, and reduce the interference level at UEs. On the other hand, handover probability is increased.

The papers [24] and [12] show that LTE-based networks can be efficiently managed by algorithms based on fuzzy logic. The idea of fuzzy logic is exploited also for handover control. For example, in [13], a fuzzy system-based handover decision is proposed. This system modifies the handover decision-related parameters to adjust the service area of an eNB. Thus, the coverage of the congested eNB is reduced while coverage of the adjacent less loaded eNBs is increased. The fuzzy system is improved by a Q-Learning to select the most appropriate action targeting either the load balancing or the handover optimization. The user dissatisfaction in terms of the call blocking ratio and call dropping ratio keep values similar to baseline schemes. However, omitting mobility related metrics and parameters (such as velocity of the UE) from the handover decision leads a performance degradation if the small cells are deployed.

Another similar handover decision algorithm based on fuzzy logic is presented in [14]. The algorithm enables to adapt fuzzy rules and membership functions according to historical data available within a tracking area. Three inputs are considered for this algorithm: RSRP, Block Error Rate and Quality of Service (QoS). The implementation demonstrates that this approach minimizes operating expenses and the number of unnecessary handovers by 20% when comparing to the standard LTE handover. An advancement of the fuzzy logic–based handover is presented in [25] where Aibinu *et al.* propose a hybrid artificial intelligent handover decision. The RSS is considered as a trigger of the handover procedure and it is accompanied by a neural system forecasting the number of users in the network. The neural network is used for a determination of the model coefficients for an effective prediction of the RSS level in the handover decision management system. However, as in the previous paper, the mobility related parameters are not taken into account. Moreover, the algorithm is of very high complexity so its suitability for the dense SCeNBs deployment is limited.

Furthermore, in [26], Hussein *et al.* propose a Fuzzy Multiple-Criteria Cell Selection (FMCCS) to optimize the handover procedure. The FMCCS method considers a fuzzy system integrated with a Technique for Order Preference by using Similarity to Ideal Solution (TOPSIS). The fuzzy-based TOPSIS is employed as a Multiple-Criteria Decision-Making (MCDM) process that performs ratings and weighting of criterions represented by linguistic variables. The handover decision considers a combination of S-criterion, where S refers to signal quality in the downlink (defined as RSRP), availability of resource blocks for data transfer, and Signal to Interference plus Noise Ratio (SINR). The results show that the FMCCS reduces frequency of ping pong handovers and handover failure ratio. The scheme is evaluated only in macrocells scenarios and there is no assurance of flexibility for dense environments.

In [15], we introduce a self-tuning handover algorithm for mobile networks with dense small cells. The proposed STHA allows to estimate if the handover to a new cell is efficient or not and avoid handovers, which are not seen beneficial. The STHA extends the common handover decision by a new fuzzy logic-based handover condition comparing the signal level from the serving eNB with a dynamic threshold of signal level. The simulation results, presented in [15], show that the proposed algorithm reduces handover failure ratio and ping pong effect.

With respect to all-above mentioned papers, the novelty of our proposal consists in design of a new handover decision scheme, which is capable of dynamic adaptation of the hysteresis margin based on a new fuzzy logic system. The system is designed so that it allows to minimize the number of redundant handovers, ping pong handovers, and handover failure ratio. Simultaneously, the time when the UEs are connected to the SCeNBs remains unimpaired so the benefits of dense SCeNBs deployment are preserved.

III. PROPOSED FUZZY LOGIC HANDOVER DECISION

In this section, a novel fuzzy logic-based scheme for dynamic adjustment of the hysteresis margin is presented. To this end, we first summarize basic principle of a general existing handover decision algorithm based on the hysteresis margin. Then, we give a high-level overview of the proposed handover decision algorithm incorporating dynamic fuzzy logic control of the hysteresis margin. Last, we provide details of the proposed algorithm including realization of the developed fuzzy logic system.

A. CONVENTIONAL HANDOVER DECISION

The conventional handover decision is based on a comparison of RSRP from the serving and neighboring eNBs [27]. The RSRP is defined as a linear average of the powers received at specific resources (reference signals) spanned over whole frequency bandwidth. The handover is triggered on the basis of the measurement reports received by the eNB from the UE. In its simple form, the handover decision is initiated if the following condition prevails for a particular period of time:

$$RSRP_{NeNB} > RSRP_{SeNB} + \Delta_{HM} \tag{1}$$

where $RSRP_{NeNB}$ and $RSRP_{SeNB}$ are the levels of RSRP from the neighboring and serving eNBs, respectively; and Δ_{HM} stands for the hysteresis margin. The purpose of Δ_{HM} is to avoid redundant ‘‘ping pong’’ handovers when the UE is continuously handed over between two eNBs.

B. PROPOSED HANDOVER DECISION WITH DYNAMIC HYSTERESIS MARGIN

In our previous work [15], the handover decision is based on a new added condition that is evaluated once common handover decision condition (1) is fulfilled. The decision condition imposes that the handover is performed only if all the inputs of the fuzzy algorithm indicate that the serving connection is not sufficient to provide the required throughput and handover to one of the neighboring cells is more advantageous. In contrast, now, we derive a dynamic hysteresis margin determined by the multi-criteria fuzzy logic system improving the handover decision in a self-optimizing manner. The fuzzy logic is efficiently used in the context of complex ill-defined processes and it is suitable to handle a large number of imprecise parameters involved in the handover decision. In this sense, we propose a mechanism capable to reduce the number of redundant handovers while keeping a high utilization of SCeNBs. The general principle of our proposal is as follows.

In the first step, the RSRP of the serving eNB is compared with the RSRP of the neighboring eNBs. Then, if any neighboring eNB offers the RSRP of a higher level than the serving eNB, the fuzzy system determines the value of the dynamic hysteresis margin. In the third step, the dynamic hysteresis margin derived by the fuzzy logic system is considered for the handover decision. These main steps of the proposed algorithm are summarized as follow:

1) Check a *preliminary condition* for triggering the process of handover decision assessment:

$$RSRP_{NeNB} > RSRP_{SeNB} \tag{2}$$

This condition avoids redundant assessment of the handover decision condition, so it can be omitted without any impact on the handover performance.
2) If (2) is fulfilled, determine the*dynamic hysteresis margin* ($\Delta_{HM,d}$) by a new fuzzy logic-based system.
3) Perform *a common handover decision* considering the new fuzzy logic-based hysteresis margin, i.e.,:

$$RSRP_{NeNB} > RSRP_{SeNB} + \Delta_{HM,d} \tag{3}$$

The first and the third steps are common for many handover decision algorithms. Thus, the main novelty lays in the second step, fuzzy logic-based system for determination of the $\Delta_{HM,d}$, which is described in the following subsection.

C. FUZZY LOGIC SYSTEM FOR DETERMINATION OF DYNAMIC HYSTERESIS

The fuzzy logic systems have been developed to manage vagueness and uncertainty in a reasoning process of an intelligent system, such as a knowledge based system, an expert system, or a logic control system [28]. The fuzzy logic systems are very useful for automatic network parameter optimization, which is composed of three basic steps: collecting data, evaluation of the data, and performing a control action. In Fig. 1, an architecture of the proposed fuzzy system is presented. To easy understanding of the proposed concept, we first explain an architecture of general fuzzy logic systems, and then, we explain its application to our handover decision problem.

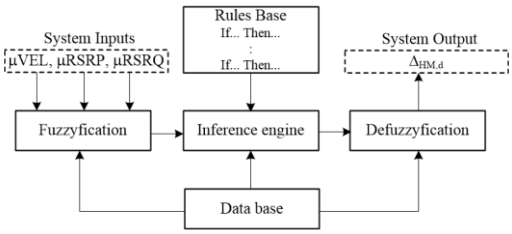

FIGURE 1. Illustration of general fuzzy logic architecture with inputs and output of the proposed fuzzy system for the handover decision algorithm.

The first step performed in the fuzzy logic system is the *fuzzification* process. In this step, the crisp inputs are translated into linguistics variables (e.g., *low, medium,high*) and a membership function is calculated for each input of the fuzzy system. The membership function is a curve that defines how each point in the input space is mapped to a membership value (or degree of membership). Typically, the membership functions are expressed in a form of mathematic functions. The fuzzification process also involves transformation of the values of input variables and a scale mapping. The scale mapping translates the range of the inputs values into corresponding universes of discourse finding the fuzzy representation of non-fuzzy input values.

The second block, *Data Base,* defines the fuzzy membership functions that allow to assign the grades of membership to the fuzzy sets. Such an assignment is built from concepts, which are subjectively defined and based on expert knowledge. The fuzzy set $\tilde{A}$ in a universe of discourse X is described by the membership function $\mu\tilde{A}(x)$ where $x \in \langle 0, 1\rangle$ and $x \in \Re$. The function value $\mu\tilde{A}(x)$ is denoted as the grade of the membership of x in $\tilde{A}$. As shown in Fig. 2, we adopt a triangular membership function for all the inputs and the output, as this function is suitable for real-time operation due to their simplicity in modeling and easy interpretation [29], [30].

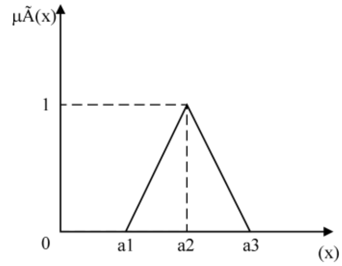

FIGURE 2. Illustration of the membership functions of a general fuzzy logic system.

A triangular fuzzy number $\tilde{A}$ can be denoted by a triplet $(a1, a2, a3)$. The mathematical form is expressed as follows:

$$\mu\tilde{A}(x) = \begin{cases} 0 & x \leq a1 \\ \dfrac{x - a1}{a2 - a1} & a1 < x \leq a2 \\ \dfrac{a3 - x}{a3 - a3} & a2 < x \leq a3 \\ 0 & x > a3 \end{cases} \tag{4}$$

The next block of the fuzzy logic system, the *Rules Base*, comprises all possible relationships among the system inputs and output. An example of a fuzzy system with two inputs *x1* and Center of Gravity *x2* (antecedents) and a single output *y* (consequent) is described by a collection of r linguistic IF–THEN propositions in the form:

$$\text{IF } x1 \text{ is } \tilde{A}_1^k \text{ and IF } x2 \text{ is } \tilde{A}_2^k \text{ THEN } y \text{ is } \tilde{B}^K \text{ for } k{=}1, 2, \ldots, r \tag{5}$$

where $\tilde{A}_1^k$ and $\tilde{A}_2^k$ are the fuzzy sets representing k-th inputs (antecedents) and $\tilde{B}^k$ is the fuzzy set representing the k-th output (consequent).

The key part of each fuzzy logic system is the *Inference engine*, which identifies rules to be triggered and calculates the fuzzy values of the output variables using a max–min inference method [31]. This method tests the magnitudes of each rule and selects the highest one. The main advantage of the max-min method is its computational simplicity. In the *Inference engine*, a fuzzy implication operator is applied to obtain a new fuzzy set based on the consequent of each rule (a fuzzy set) and obtained antecedent value. Then, the outputs obtained for each rule are combined into a single fuzzy set using a fuzzy aggregation operator. In other words, the rule with the highest degree of truth is selected and then, the consequent membership function to be activated is determined. The output (consequent) is given by:

$$\mu_{\tilde{B}_k}(y) = \max_k \left[\min\left[\mu_{\tilde{A}_1^k}(VEL), \mu_{\tilde{A}_2^k}(RSRP), \mu_{\tilde{A}_3^k}(RSRQ)\right]\right] \quad \text{for } k = 1, 2, \ldots, r \tag{6}$$

Finally, the *Defuzzification* process, which has the opposite meaning of the *Fuzzification*, provides a non-fuzzy control action from an inferred fuzzy control action. This step consists in a transformation of the aggregated fuzzy

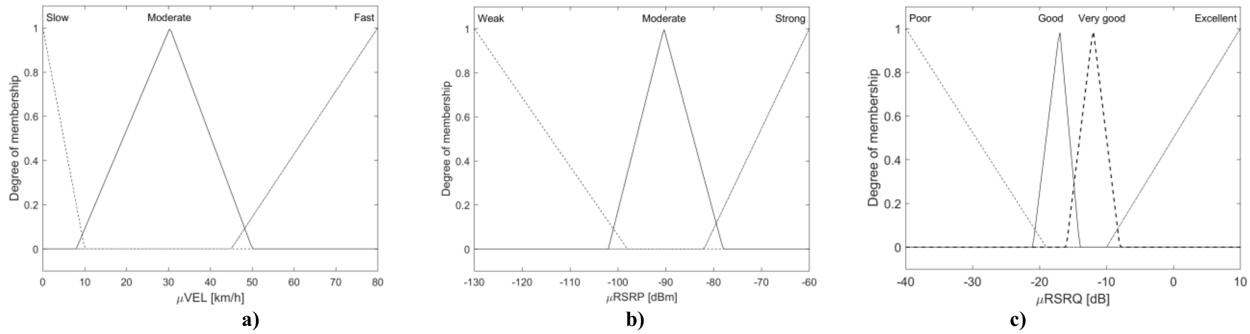

FIGURE 3. Membership functions for inputs: (a) μVEL, (b) $\mu RSRP$, and (c) $\mu RSRQ$.

set $\mu_{\tilde{B}_k}(y)$ into one single crisp number. This transformation corresponds to the determination of the Center of Gravity (COG) [32]. The weighted average of the membership function or the center of gravity of the area bounded by the membership function is computed as follows:

$$\mu_{\tilde{B}_k}(y) = \frac{\sum_{i=1}^{N} \mu_{\tilde{B}(y)y}}{\sum_{i=1}^{N} \mu_{\tilde{B}(y)}} \tag{7}$$

where $\mu_{\tilde{B}(y)y}$ is the centroid of each symmetric membership function.

In our proposal, we consider three inputs in the *Fuzzification* process: UE' velocity, RSRP, and RSRQ. The first input parameter is the UE's velocity denoted as μVEL. High-speed UEs may pass through the SCeNB in a short time interval, causing frequent handover leading to a massive handover signaling overhead to the network [33]. In Fig. 3a, we express the characterization of the three sets of the UE's velocity: *Slow* (from 0 to 10 km/h), *Moderate* (from 8 to 50 km/h), and *Fast* (from 45 to 80 km/h). It is important to notice that the membership functions are overlapping due to the smooth transition boundary, which is an underlying characteristic of the fuzzy sets; i.e., the precise input values during fuzzification process can belong to more than one fuzzy set with the different degree of membership shown in individual membership functions of each parameter.

As the second input, we consider a received signal power represented by RSRP, denoted as $\mu RSPR$, considering following three states (defined based on a common range of RSRP in 3GPP): *Weak* (-160 to -95 dBm), *Moderate* (-100 to -73 dBm), and *Strong* (-80 to -20 dBm), as shown in Fig. 3b. With the aim to define a suitable eNB for handover, the RSRP measurement provides an indication of the eNB coverage, and the received signals strengths that is required for the handover decision.

Furthermore, considering scenarios with the dense SCeNB deployment, an efficiency of the radio communication depends not only to the signal level from the serving eNB, but also on noise and interference caused by the neighboring eNBs. Thus, parameter RSRQ (denoted as $\mu RSRQ$) is considered as the third input. Fig. 3c shows the sets of $\mu RSRQ$ defined in the following way: *Poor* (from -60 to -18 dB), *Good* (from -22 to -12 dB), *Very Good* (from -14 to -6 dB), and *Excellent* (from -10 to $+20$ dB) with respect to definition of the range of RSRQ in 3GPP.

The intervals and granularity of all input parameters are defined based on the ranges of values commonly expected in mobile networks as assumed in 3GPP [34].

All three inputs are combined by the *Inference Engine* into the output of the proposed fuzzy system represented by $\Delta_{HM,d}$. Four fuzzy sets are defined for the output $\Delta_{HM,d}$ to achieve a reasonable granularity in the output space (see Fig. 4): *Very low* (from 1 to 4.5 dB), *Low* (from 3.5 to 7 dB), *Average* (from 6 to 9.5 dB), and *High* (from 8.5 to 12 dB).

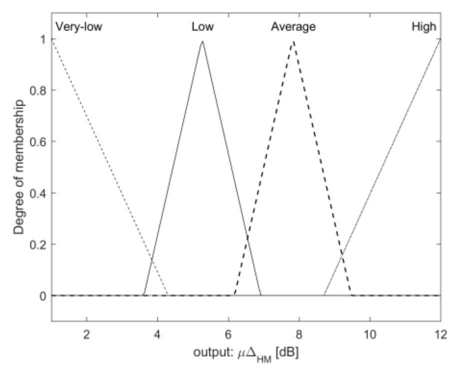

FIGURE 4. Membership function for the output of the proposed fuzzy logic system $\Delta_{HM,d}$.

We formulate 36 fuzzy rules (the number of rules is determined by the combination of all possible states of all three input variables, i.e., *3 x 3 x 4*). The rules are defined considering following aspects and requirements:

- If μVel is *Low* the $\Delta_{HM,d}$ should be set to lower values to provide a freedom to find the most suitable eNBs. On the other hand, if the μVel is *High* the $\Delta_{HM,d}$ should be set to higher values to avoid the premature handover. In this case, it is preferred to temporary tolerate a suboptimal connection rather than perform unnecessary handovers.
- If $\mu RSRP$ is *Weak* the $\Delta_{HM,d}$ should be set to lower values to facilitate the handover, while if the $\mu RSRP$ is

TABLE 1. Rules formulated for determination of $\mu\Delta_{HM,d}$.

Rule No.	μVEL	$\mu RSRP$	$\mu RSRQ$	$\mu\Delta_{HM,d}$
1	Low	Weak	Poor	Very Low
2	Low	Weak	Good	Very Low
3	Low	Weak	Very good	Very Low
4	Low	Weak	Excellent	Very Low
5	Low	Moderate	Poor	Very Low
6	Low	Moderate	Good	Very Low
7	Low	Moderate	Very good	Very Low
8	Low	Moderate	Excellent	Low
9	Low	Strong	Poor	Very Low
10	Low	Strong	Good	Very Low
11	Low	Strong	Very good	Low
12	Low	Strong	Excellent	Average
13	Medium	Weak	Poor	Very Low
14	Medium	Weak	Good	Low
15	Medium	Weak	Very good	Low
16	Medium	Weak	Excellent	Average
17	Medium	Moderate	Poor	Very Low
18	Medium	Moderate	Good	Low
19	Medium	Moderate	Very good	Low
20	Medium	Moderate	Excellent	Average
21	Medium	Strong	Poor	Very Low
22	Medium	Strong	Good	Low
23	Medium	Strong	Very good	Average
24	Medium	Strong	Excellent	High
25	High	Weak	Poor	Low
26	High	Weak	Good	Average
27	High	Weak	Very good	Average
28	High	Weak	Excellent	Average
29	High	Moderate	Poor	Average
30	High	Moderate	Good	High
31	High	Moderate	Very good	High
32	High	Moderate	Excellent	High
33	High	Strong	Poor	Average
34	High	Strong	Good	High
35	High	Strong	Very good	High
36	High	Strong	Excellent	High

Strong the $\Delta_{HM,d}$ should be set to higher values to keep the current connection.

- If $\mu RSRQ$ is *Poor* the $\Delta_{HM,d}$ should be set to lower values to facilitate the handover since there are no advantages of insisting on a bad connection. On the other hand, if the $\mu RSRQ$ is *Excellent* the $\Delta_{HM,d}$ should be set to higher values to maintain the connection experience.

TABLE 1 shows the rules and consequent definition of the $\mu\Delta_{HM,d}$.

Individual steps of our proposed fuzzy logic based handover decision algorithm (by means of determination of adaptive hysteresis margin $\Delta_{HM,,d}$ are summarized in Algorithm 1.

IV. PERFOMANCE EVALUATION METHODOLOGY

In this section, models, scenarios, and deployment used for performance evaluations are presented. Afterwards, the performance metrics are defined. Then, the last subsection describes the competitive state of the art algorithms considered for the performance comparison.

Algorithm 1 Proposed Handover Decision Algorithm With Fuzzy Logic-Based Determination of Dynamic Hysteresis Margin

1. *IF* $RSRP_{NeNB} > RSRP_{SeNB}$
2. Converts $\{\mu VEL, \mu RSRP$ and $\mu RSRQ\}$ to fuzzy sets
3. Calculate the degree of truth for each fuzzy rule acc. to (4)
4. Computes the antecedent of each k rule by implication operator:
   $\mu_{\tilde{B}_k}(y) = \min\left[\mu_{\tilde{A}_1^k}(VEL), \mu_{\tilde{A}_2^k}(RSRP), \mu_{\tilde{A}_3^k}(RSRQ)\right]$
5. Calculate the outputs of each triggered rule acc. to the proposed rule base and the membership functions of the output defined in TABLE 1
6. Aggregate outputs obtained for each rule into a single fuzzy set:
   $\mu\tilde{\Delta}_{HM,d} = \max_k \left[\mu_{\tilde{B}k}(y)\right]$
7. Transform the output value of $\mu\tilde{\Delta}_{HM,d}$ into a crisp value $\Delta_{HM,d}$ by center of gravity method acc.to (7)
8. *IF* $RSRP_{NeNB} > RSRP_{SeNB} + \Delta_{HM,d}$
9. PERFORM handover
10. *ELSE* DO NOT PERFORM handover
11. *END*

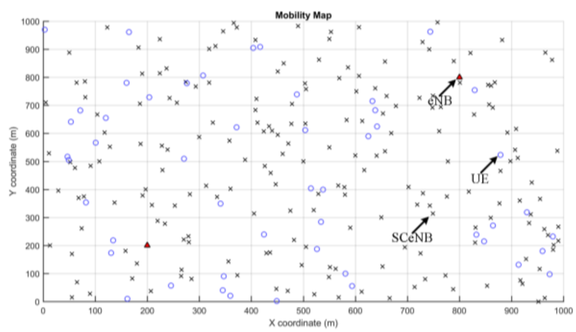

FIGURE 5. Example of the simulation deployment with eNBs represented by red triangles, SCeNBs by black crosses, and UEs by blue circles.

A. SIMULATION MODELS AND SCENARIOS

The simulations are performed in MATLAB. We assume an area with a size of 1000 m *x* 1000 m. Within this area, two eNBs, up to 200 SCeNBs, and 50 UEs are deployed as depicted on an example in Fig. 5. The SCeNBs and the UEs are randomly dropped with a uniform distribution at the beginning of the simulation while both eNBs are located at predefined positions close to the area's corners so that these eNBs can provide coverage for the whole simulation area. The UEs move according to the random waypoint mobility model (see [35] for more details). For variability, the speed is randomly selected in a range from 0 to 80 km/h.

TABLE 2. Simulation parameteres.

Parameters	Value
Simulation Area	1000x1000m
Carrier Frequency	2 GHz
Transmission power of eNB/SCeNB	43/20 dBm
Number of eNB/SCeNB/UEs	2/200/50
Path loss model from eNB/SCeNB	Okumura Hata Model/ITU-R P1238
Number of sectors per eNB	1 sector (Omnidirectional antennas)
Heigh of antenna for eNB/UEs	30/1.5
Mobility Model	Random Waypoint Mobility
Simulation Time	900 s per drop
Number of simulation drops	25 drops

The signal propagation from the base stations to the UEs is derived according to the models recommended by Small Cells Forum. Hence, Okumura-Hata and ITU-R P.1238 models are used for the signal propagation from the eNBs and the SCeNBs, respectively. The major simulation parameters are summarized in TABLE 2.

B. PERFORMANCE METRICS

Following metrics are considered for the performance assessment and comparison of the performance with competitive solutions: *Average number of performed handovers*, *Handover failure ratio*, *Ping pong ratio*, and *Time spent in SCeNBs*.

The *average number of handovers* ($N_{HO,AVG}$) is calculated as a sum of the number of handovers performed by all UEs (N_{HO}) over the total number of the UEs in the simulation (N_{UE}).

$$N_{HO,AVG} = \frac{N_{HO}}{N_{UE}} \tag{8}$$

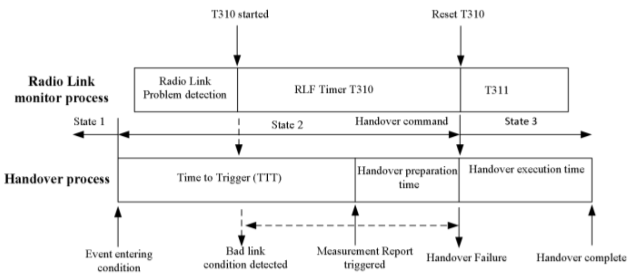

FIGURE 6. Illustration of radio link monitoring process and handover process for determination of handover failure [36].

For modelling of the *handover failure ratio*, the handover procedure is divided into three states according to LTE [36], as shown in Fig. 6. The *Stage 1* is defined by the instant that precedes the *Event A3* condition in 3GPP. In *Stage 2*, the UE triggers the measurement reporting if the *Event A3* condition holds throughout the time-to-trigger duration. *Stage 3* occurs when the UE successfully receives handover command from the serving eNB and starts the handover execution process. In our case, the handover failure events are determined acording to the downlink SINR. As in LTE-A, we assume that when SINR is lower than the threshold Qout, a bad channel condition is indicated and the T310 times is started. The handover failure is declared when T310 expires.

Then, the *handover failure (HF) ratio*, is defined as a ratio between the number of handover failures (N_{fail}) and the number of all handover attempts. The number of handover attempts is given by the sum of the number of the failed handover and the number of successful handovers (N_{suc}):

$$HF = \frac{N_{fail}}{N_{fail} + N_{suc}} \tag{9}$$

The third metric, the *handover ping pong (HPP) ratio*, is defined as follows. If a connection is handed over to a new (SC)eNB and handed back to the original (SC)eNB in less than a critical time, denoted as minimum time-of-stay (t_{MTS}), the handover is considered as the ping pong handover. The ping pong handover ratio represents the number of ping pong handovers (N_{PP}) divided by the total number of handovers including: i) the number of ping pong handovers, ii) the number of handovers without ping pong (N_{nPP}), i.e., with stay longer than t_{MTS}, and iii) the number of failed handovers (N_{fail}). Then, the *HPP* is formulated as:

$$HPP = \frac{N_{nPP}}{N_{nPP} + N_{PP} + N_{fail}} \tag{10}$$

Last, the relative *time spent in small cells* (t_{SCeNB}) is understood as an average duration of the connection of the UEs to the SCeNBs (t_{connSC}) over the simulation time (t_{sim}):

$$t_{SCeNB} = \frac{\left(\frac{\sum t_{connSC}}{N_{UE}}\right)}{t_{sim}} \tag{11}$$

C. COMPETITIVE ALGORITHMS

In our simulations, the proposed handover algorithm is compared with three competitive schemes and with our previous work to demonstrate the superiority of the proposal. The following state of the art algorithms implemented for the performance comparison are considered:

- *Best Connection (BC)* representing the case when the UE is always connected to the (SC)eNB providing the highest RSRP.
- *Conventional LTE handover* (in figures denoted as LTE) is implemented according to 3GPP as defined in [37].
- *Fuzzy Multiple-Criteria Cell Selection (FMCCS)* defined in [26] is based on fuzzy logic integrated with TOPSIS.
- *Self-Tuning Handover Algorithm (STHA)* defined in [15] adds a new fuzzy-based handover condition on the top of convention handover condition to improve handover decision. This algorithm is our former work, which serves as a basement for the algorithm developed in this paper. Thus, we include it to demonstrate superiority of the new proposal with respect to STHA.

V. PERFORMANCE EVALUATION

In this section, the results of simulations are presented to provide a comparison of the performance with respect to the competitive approaches. This section is divided into two subsections. In the first subsection, the performance of the proposed and competitive algorithms is compared and discussed. Then, we evaluate the impact of fuzzy logic system inputs on the performance of our algorithm.

A. COMPARISON OF PERFORMANCE WITH COMPETITIVE ALGORITHMS

First, we investigate an impact of the number of SCeNBs on the average number of handovers performed by the UEs (see Fig. 7). As can be expected, the number of handovers increases with the number of SCeNBs, because more cell edges appear in the network and the UEs are forced to perform handover more often to avoid connection losses. The proposed algorithm significantly outperforms all compared schemes thanks to the smart adaptation of the hysteresis margin allowing to mitigate redundant handovers. The gain introduced by the proposed algorithm increases with the number of SCeNBs and reaches 18%, 22%, 33% and 52% improvement comparing to STHA, FMCCS, LTE and BC algorithms, respectively, for 200 SCeNBs deployed in the simulation area.

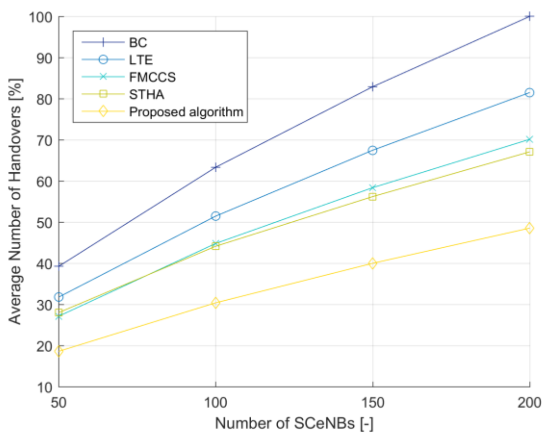

FIGURE 7. Impact of the number of SCeNBs on the average number of handovers performed by the UEs.

In Fig. 8, the handover failure ratio is depicted. It can be seen that the HF ratio increases with the number of SCeNBs. This increase is caused by a stronger interference imposed in the scenario with more SCeNBs leading to rapid drops in SINR and consequent failures of the handover. The figure further shows that, for the low densities of the SCeNBs (roughly up to 100 SCeNBs), the proposed algorithm reaches similar performance as our previous work – the STHA. Both the proposed algorithm and STHA outperform all three competitive algorithms and lower the HF ratio to almost a half. For higher numbers of the SCeNBs (more than 100), the performance of STHA is getting worse and converges to the FMCCS (i.e., to HF ratio about 4.5%). Contrary, the proposed

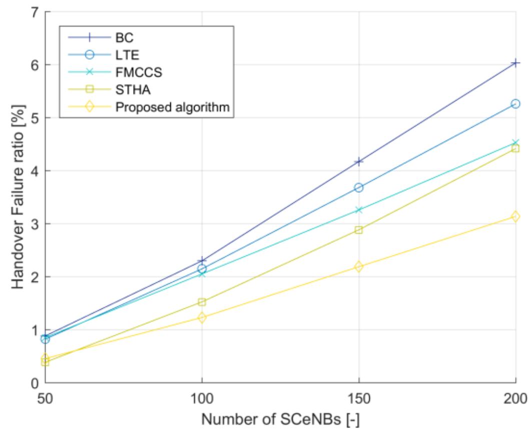

FIGURE 8. Impact of the number of SCeNBs on the handover failure ratio.

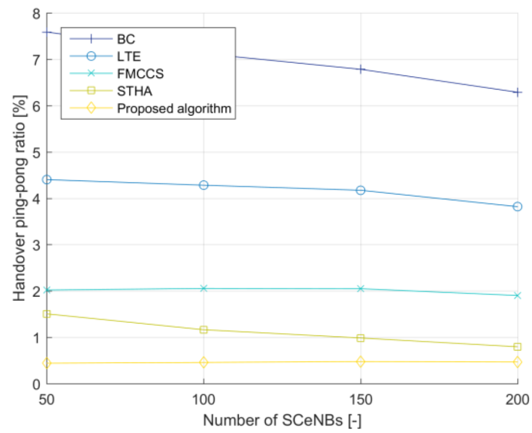

FIGURE 9. Impact of the number of SCeNBs on the handover ping pong ratio for $t_{MTS} = 2$s.

algorithm is still able to keep low HF ratio (around 3%) even for 200 SCeNBs.

An impact of the number of SCeNBs on the ping pong effect (represented by the HPP ratio) is illustrated in Fig. 9 for $t_{MTS} = 2$s. This figure shows superiority of the proposed algorithm, which keeps the HPP ratio always below 0.5% for all investigated numbers of SCeNBs. This eminent performance is achieved by the fact that our proposal optimizes the handover hysteresis margin directly related to the diminished ratio of unnecessary handovers. In contrast, the competitive solutions lead to a relatively high HPP ratio (1.5%, 2%, 4.4%, and 7.5%, for STHA, FMCCS, LTE, and BC, respectively) for low to medium densities of the SCeNBs (up to 50 SCeNBs). The HPP of all four competitive solutions lowers for a higher density of the SCeNBs. This decrease is due to the fact that with the higher density of the SCeNBs, the probability that the connection is handed over to a new SCeNBs is increased comparing to the probability of the handover back to the former serving SCeNB. Nevertheless, even for 200 SCeNBs, the HPP ratio is still at 0.7%, 1.9%, 3.8%, and 6.2% for the STHA, FMCCS, LTE, and BC algorithms, respectively, while the proposed scheme keeps the HPP ratio at 0.4%.

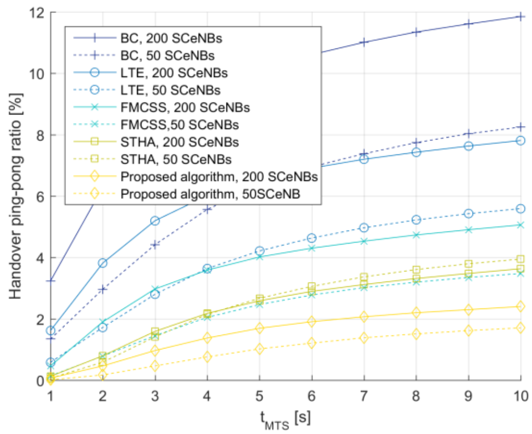

FIGURE 10. Impact of t_{MTS} on the ping pong ratio for 200 SCeNBs (solid lines) and 50 SCeNBs (dashed lines).

As the ping pong effect is defined by the t_{MTS}, we also demonstrate the impact of t_{MTS} on the HPP ratio in Fig. 10. The HPP ratio increases with t_{MTS}, because more handovers are considered as ping pong with increasing t_{MTS}. We can see that the reduction in HPP ratio demonstrated in Fig. 9, is valid for a wide range of t_{MTS} and the proposed algorithm outperforms all competitive schemes disregarding the t_{MTS}.

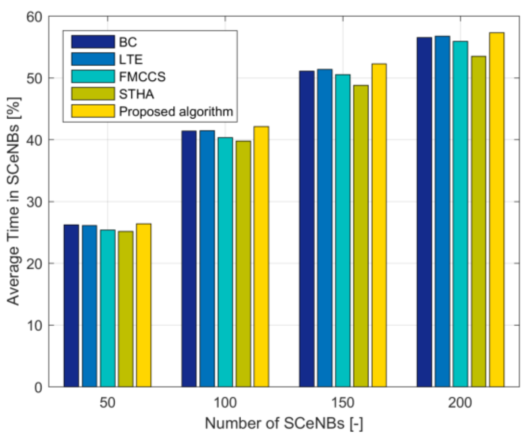

FIGURE 11. Average time spent by the UEs connected to the SCeNBs.

Last, we analyze the *average time spent by the UEs connected to the SCeNBs*. Many handover algorithms focus on the mitigation of handovers while decreasing the time when the UEs are connected to the SCeNBs. Nevertheless, this mitigation leads to an underutilization of resources provided by the SCeNBs and consequently to a loss in the potential of the SCeNBs to improve network throughput. As we can see in Fig. 11, our proposal even slightly improves the time spent by the UEs in SCeNBs comparing to all competitive algorithms. The most notable gain (from 1% to 4% depending of the number of SCeNBs) is introduced with respect to the STHA, which reaches the closest performance in all other investigated performance metrics. The prolongation of the time spent in SCeNBs is introduced by the combination of all three inputs of the fuzzy system resulting in the hysteresis margin that is adapted according to channel quality.

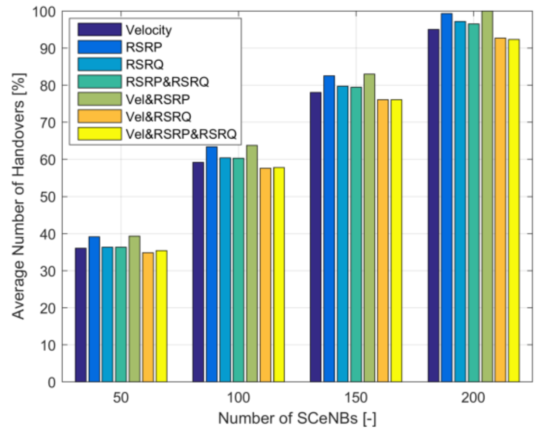

FIGURE 12. Impact of inputs to the fuzzy logic system (RSRP, RSRQ, velocity) on the average number of performed handovers.

B. IMPACT OF FUZZY SYSTEM IMPUTS ON THE PERFORMANCE

In this subsection, we evaluate and discuss the impact of individual inputs to the fuzzy system and their combinations in order to identify an importance of the inputs on the overall performance. As in previous subsection, four performance metrics, *Average Number of Handovers, Handover Failure ratio, Ping pong ratio and Average time in SCeNBs*, are considered and investigated.

In Fig. 12, the *average number of performed handovers* is shown. We can see that the velocity and RSRQ are key inputs to the fuzzy logic system. The combination of velocity and RSRQ leads to the lowest number of handovers and inclusion of RSRP do not change this performance metrics notably, because, from the handover decision point of view, RSRQ already includes information about RSRP.

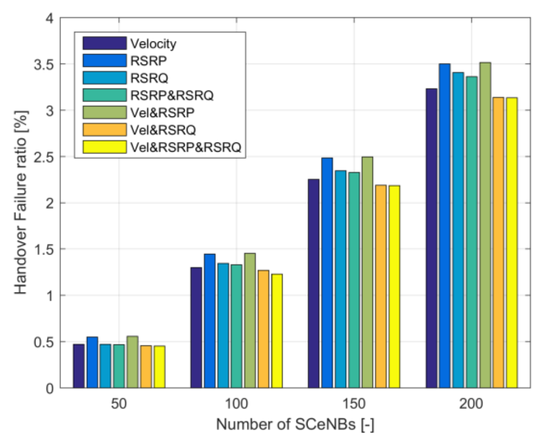

FIGURE 13. Impact of inputs to the fuzzy logic system (RSRP, RSRQ, velocity) on the handover failure ratio.

The impact of various combinations of the inputs on HF ratio is depicted in Fig. 13. Like in previous figure, the

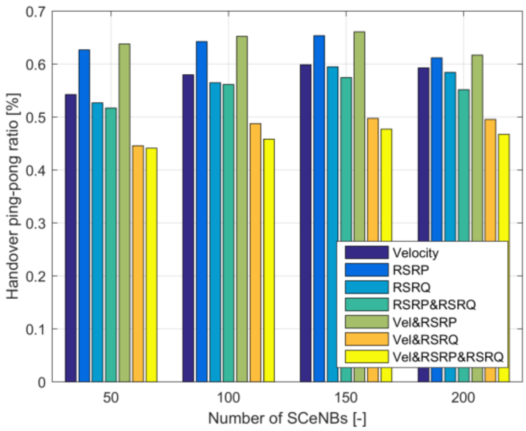

FIGURE 14. Impact of inputs to the fuzzy logic system (RSRP, RSRQ, velocity) on the handover ping pong ratio.

velocity and RSRQ are of the major importance for the HPP ratio and improvement introduced by further inclusion of the RSRP is negligible as the key information related to the HF (i.e., channel quality) is already covered by the RSRQ.

In Fig. 14, we analyze the impact of the fuzzy logic system inputs on HPP ratio. In this case, we can see that the performance gain is generated again by a combination of velocity and RSRQ; however, RSRP can further improve the HPP ratio for higher densities of SCeNBs notably. The RSRP provides the UE with essential information about the strength of signal from the serving and neighboring cells. This helps to determine the optimum time for handover and to avoid ping pong if the handover is not necessary.

Last, the impact of various combinations of the inputs on *time spent in small cells* is depicted in Fig. 15. We can observe minor variation of the time for all input combinations.

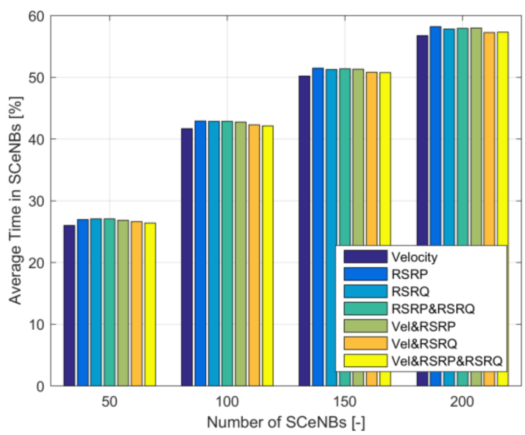

FIGURE 15. Impact of inputs to the fuzzy logic system (RSRP, RSRQ, velocity) on the average time spent by the UEs connected to the SCeNBs.

From the analysis of all three inputs, we can conclude that the velocity of the UE and RSRQ are the most important inputs for the proposed fuzzy logic system. However, consideration of the third inputs, RSRP, is useful for reduction of the ping-pong ratio in scenarios with the dense SCeNBs.

VI. CONCLUSIONS

In this paper, we have introduced a novel handover decision algorithm exploiting new fuzzy logic system for dynamic determination of the hysteresis margin. The proposed algorithm leads to a superior performance improving key handover performance indicators comparing to state of the art solutions. The proposed solution almost eliminates handover ping pong effect and, besides, it also reduces the handover failure ratio and the total number of handovers comparing to the state of the art algorithms. With respect to the competitive solutions, the achieved improvements are not at the cost of reduced time spent by the UEs in the SCeNBs. The proposed algorithm keeps the time spent in the SCeNBs at the same level as the algorithms, which demonstrate worse performance in terms of the number of handover, ping pong ratio and handover failure ratio. Thus, the proposed algorithm allows to preserve the benefits of the SCeNBs while all key handover performance indicators are notably improved. This indicates suitability of the proposed algorithm for future mobile networks with a very high density of the SCeNBs.

In the future work, the research should focus on a prediction of a signal level for determination of the throughput gain and investigate the potential improvements regarding handover performance indicators.

REFERENCES

[1] P.-H. Huang, H. Kao, and W. Liao, "Cross-tier cooperation for optimal resource utilization in ultra-dense heterogeneous networks," *IEEE Trans. Veh. Technol.*, vol. 66, no. 12, pp. 11193–11207, Dec. 2017.
[2] D. Xenakis, N. Passas, L. Merakos, and C. Verikoukis, "Handover decision for small cells: Algorithms, lessons learned and simulation study," *Comput. Netw.*, vol. 100, pp. 64–74, May 2016.
[3] R. Ahmad, E. A. Sundararajan, N. E. Othman, and M. Ismail, "Handover in LTE-advanced wireless networks: State of art and survey of decision algorithm," *Telecommun. Syst.*, vol. 66, no. 3, pp. 533–558, 2017.
[4] P. Munoz, R. Barco, and I. de la Bandera, "On the potential of handover parameter optimization for self-organizing networks," *IEEE Trans. Veh. Technol.*, vol. 62, no. 5, pp. 1895–1905, Jun. 2013.
[5] T. Levanen, J. Pirskanen, and M. Valkama, "Dense small-cell networks: Rethinking the radio interface beyond LTE-advanced," in *Proc. Int. Conf. 5G Ubiquitous Connectivity*, Nov. 2014, pp. 163–169.
[6] J. G. Andrews, X. Zhang, G. D. Durgin, and A. K. Gupta, "Are we approaching the fundamental limits of wireless network densification?" *IEEE Commun. Mag.*, vol. 54, no. 10, pp. 184–190, Oct. 2016.
[7] N. Panwar, S. Sharma, and A. K. Singh, "A survey on 5G: The next generation of mobile communication," *Phys. Commun.*, vol. 18, pp. 64–84, Mar. 2016.
[8] Y. Sun, Y. Chang, M. Hu, and T. Zeng, "A universal predictive mobility management scheme for urban ultra-dense networks with control/data plane separation," *IEEE Access*, vol. 5, pp. 6015–6026, 2017.
[9] M. Vondra and Z. Becvar, "Distance-based neighborhood scanning for handover purposes in network with small cells," *IEEE Trans. Veh. Technol.*, vol. 65, no. 2, pp. 883–895, Feb. 2016.
[10] M. Mehta, N. Akhtar, and A. Karandikar, "Impact of handover parameters on mobility performance in LTE HetNets," in *Proc. 21st Nat. Conf. Commun.*, Feb./Mar. 2015, pp. 1–6.
[11] K. Kitagawa, T. Komine, T. Yamamoto, and S. Konishi, "A handover optimization algorithm with mobility robustness for LTE systems," in *Proc. IEEE PIMRC*, Sep. 2011, pp. 1647–1651.
[12] Q. Kuang, J. Belschner, Z. Bleicher, H. Droste, and J. Speidel, "A measurement-based study of handover improvement through range expansion and interference coordination," *Wireless Commun. Mobile Comput.*, vol. 15, no. 14, pp. 1784–1798, 2015.

[13] P. Muñoz, R. Barco, and I. de la Bandera, "Load balancing and handover joint optimization in LTE networks using fuzzy logic and reinforcement learning," *Comput. Netw.*, vol. 76, pp. 112–125, Jan. 2015.
[14] C. F. Kwong, T. C. Chuah, S. W. Tan, and A. Akbari-Moghanjoughi, "An adaptive fuzzy handover triggering approach for long-term evolution network," *Expert Syst.*, vol. 33, no. 1, pp. 30–45, 2016.
[15] K. C. Silva, Z. Becvar, E. Cardoso, C. R. L. Francês, "Self-tuning handover decision based on fuzzy logic in mobile networks with dense small cells," in *Proc. IEEE WCNC*, Apr. 2018, pp. 1–6. [Online]. Available: http://5gmobile.fel.cvut.cz/Papers~/WCNC18_STHA_Fuzzy.pdf
[16] Z. Becvar and P. Mach, "Mitigation of redundant handovers to femtocells by estimation of throughput gain," *Mobile Inf. Syst.*, vol. 9, no. 4, pp. 315–330, 2013.
[17] M.-H. Song, S.-H. Moon, and S.-J. Han, "Self-optimization of handover parameters for dynamic small-cell networks," *Wireless Commun. Mobile Comput.*, vol. 15, no. 11, pp. 1497–1517, Aug. 2015.
[18] P. Lin, L. F. G. Casanova, and B. K. S. Fatty, "Data-driven handover optimization in next generation mobile communication networks," *Mobile Inf. Syst.*, vol. 2016, 2016, Art. no. 2368427.
[19] D.-W. Lee, G.-T. Gil, and D.-H. Kim, "A cost-based adaptive handover hysteresis scheme to minimize the handover failure rate in 3GPP LTE system," *EURASIP J. Wireless Commun. Netw.*, vol. 2010, Dec. 2010, Art. no. 750173.
[20] C. Fischione, G. Athanasiou, and F. Santucci, "Dynamic optimization of generalized least squares handover algorithms," *IEEE Trans. Wireless Commun.*, vol. 13, no. 3, pp. 1235–1249, Mar. 2014.
[21] S. Sesia, I. Toufik, and M. Baker, *LTE-the UMTS Long Term Evolution From Theory to Practice*. Hoboken, NJ, USA: Wiley, 2009.
[22] B. Davaasambuu, K. Yu, and T. Sato, "Self-optimization of handover parameters for long term evolution with dual wireless mobile relay nodes," *Future Internet*, vol. 7, no. 2, pp. 196–213, Jun. 2015.
[23] D. Xenakis, N. Passas, L. Merakos, and C. Verikoukis, "Energy-efficient and interference-aware handover decision for the LTE-Advanced femtocell network," in *Proc. IEEE Int. Conf. Commun. (ICC)*, Jun. 2013, pp. 2464–2468.
[24] M. Ahmad, A. Saleem, K. Hesham, and N. Javaid, "A survey on fuzzy logic applications in wireless and mobile communication for LTE networks," in *Proc. 10th Int. Conf. Complex, Intell., Softw. Intensive Syst.*, Jul. 2016, pp. 76–82.
[25] A. M. Aibinu, A. J. Onumanyi, A. P. Adedigba, M. Ipinyomi, T. A. Folorunso, and M. J. E. Salami, "Development of hybrid artificial intelligent based handover decision algorithm," *Int. J. Eng. Sci. Technol.*, vol. 20, no. 2, pp. 381–390, Apr. 2017.
[26] Y. S. Hussein, B. M. Ali, M. F. A. Rasid, A. Sali, and A. M. Mansoor, "A novel cell-selection optimization handover for long-term evolution (LTE) macrocellusing fuzzy TOPSIS," *Comput. Commun.*, vol. 73, pp. 22–33, Jan. 2016.
[27] *Technical Specifiction Group Radio Acess Network; Mobility Enhancements in Heterogeneous Networks (Release 11)*, document TR 36.839 V11.1.0, 3rd Generation Partnership Project, Dec. 2012.
[28] L. A. Zadeh, "Fuzzy Sets," *Inf. Control*, vol. 8, no. 3, pp. 338–353, 1965.
[29] J. Jantzen, *Foundations of Fuzzy Control: A Practical Approach*. Hoboken, NJ, USA: Wiley, 2013.
[30] W. Pedrycz, "Why triangular membership functions?" *Fuzzy Sets Syst.*, vol. 64, no. 1, pp. 21–30, 1994.
[31] T. Ross, *Fuzzy Logic With Engineering Applications*. Hoboken, NJ, USA: Wiley, 2010.
[32] Y. Bai, H. Zhuang, and D. Wang, *Advanced Fuzzy Logic Technologies in Industrial Applications*. London, U.K.: Springer-Verlag, 2006.
[33] Q. Shen, J. Liu, Z. Huang, X. Gan, Z. Zhang, and D. Chen, "Adaptive double thresholds handover mechanism in small cell LTE-A network," in *Proc. IEEE WCSP*, Oct. 2014, pp. 1–6.
[34] *Technical Specification Group Radio Access Network; Evolved Universal Terrestrial Radio Access (E-UTRA); Requirements for Support of Radio Resource Management*, document TS 36.133, v.14.4.0, 3GPP, Aug. 2017.
[35] E. Hyytiä and J. Virtamo, "Random waypoint mobility model in cellular networks," *Wireless Netw.*, vol. 31, no. 2, pp. 177–188, 2007.
[36] *Technical Specification Group Radio Acess Network; Mobility Enhancements in Heterogeneous Networks (Release 11)*, document TR 36.839 V11.1.0, 3rd Generation Partnership Project, Dec. 2012.
[37] *Evolved Universal Terrestrial Radio Access (E-UTRA); Radio Resource Control (RRC); Protocol Specification*, document TS 36.331, 3GPP, Jul. 2011.

KETYLLEN DA COSTA SILVA received the B.Sc. degree in computer science from Amazon University in 2010 and the M.Sc. degree in electrical engineering with emphasis in applied computing from the Federal University of Pará in 2014, where she is currently pursuing the Ph.D. degree. She was on internship with Czech Technical University in Prague, Czech Republic, in 2017. She is currently a member of LPRAD (Laboratory of High Performance Network). Her research interests include radio access technologies, performance evaluation, mobility management, and heterogeneous networks.

ZDENEK BECVAR (M'08–SM'17) received the M.Sc. and Ph.D. degrees in telecommunication engineering from Czech Technical University (CTU) in Prague, Czech Republic, in 2005 and 2010, respectively. He is currently an Associate Professor with the Department of Telecommunication Engineering, CTU in Prague, Czech Republic.

From 2006 to 2007, he joined Sitronics R&D Center, Prague, focusing on speech quality in VoIP. Furthermore, he was involved in research activities of Vodafone R&D Center, CTU in Prague, in 2009. He was on internships with Budapest Politechnic, Hungary, in 2007, CEA-Leti, France, in 2013, and EURECOM, France, in 2016. In 2013, he become representative of the Czech Technical University in Prague in ETSI and 3GPP standardization organizations. In 2015, he founded 5Gmobile research laboratory at CTU in Prague, focusing on research towards 5G mobile networks and beyond.

He has published four book chapters and over 60 conference or journal papers. He is involved in the development of solutions for future mobile networks (5G and beyond) with special focus on optimization of mobility and radio resource management, device-to-device communication, self-optimization, power control, architecture of radio access network, and small cells. He is a member of more than 15 program committees at international conferences or workshops.

CARLOS RENATO LISBOA FRANCES received the B.S. degree in computer science from the Federal University of Pará (UFPA), in 1995, the M.S. and Ph.D. degrees from the University of São Paulo, Brazil, in 1998 and 2001, respectively. He held a Postdoctoral position with the Institute for Systems and Computer Engineering, Technology and Science, Porto, Portugal, in 2012. He is currently an Associate Professor with the Telecommunication and Computer Engineering Department, UFPA. His research interests include performance evaluation, optimization, Markov processes, and artificial intelligence models.