Received 23 September 2022, accepted 7 October 2022, date of publication 19 October 2022, date of current version 26 October 2022.

Digital Object Identifier 10.1109/ACCESS.2022.3215684

SURVEY

Advanced Mobility Robustness Optimization Models in Future Mobile Networks Based on Machine Learning Solutions

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This work was supported in part by the 2232 International Fellowship for Outstanding Researchers Program of TÜBİTAK through Istanbul Technical University (ITU), Turkey, under Project 118C276. The authors would also like to acknowledge the support provided by the Ministry of Higher Education Malaysia (MOHE) under the Fundamental Research Grant Scheme (FRGS/1/2019/TK04/UTM/02/34), and in part by Universiti Teknologi Malaysia (UTM) under the Collaborative Research Grant (CRG) of R.J130000.7351.4B468, and the Higher Institution Centre of Excellence (HICOE) Grants of R.J130000.7851.4J413 and R.J130000.7851.4J493.

ABSTRACT Ultra-dense heterogeneous networks (HetNets) are deployment scenarios in the advent of fifth generation (5G) and beyond network generations. A massive number of small base stations (SBSs) and connected devices have been exponentially increasing. This has subsequently led to a rise of several mobility management issues which require optimization techniques to avoid performance degradation. Machine learning (ML) is a promising approach for future mobile communication networks (5G and beyond). It has the ability of improving the efficiency of complicated heterogeneous and decentralized networks. ML has proven to be significant in the mobility management field since it optimizes handover control parameters (HCPs) over various dynamic environments. To the best of the authors' knowledge, no comprehensive survey deeply discussing a state-of-the-art ML algorithms in mobility robustness optimization (MRO) functions. However, each summarized algorithm in this study includes deployment scenario, ML type, methodology used, criteria, HCPs, key performance indicators (KPIs), simulators, and achievements which can assist researchers for future investigations in MRO functions. In addition, this study serves as a guide in the selection of proper optimization algorithms according to the outcomes of each algorithm. Furthermore, this study presented the common types of ML and the techniques used from each type to optimize the HCPs of the MRO functions. Moreover, high-mobility-aware and network topologies are presented in MRO function for further system enhancements. Besides, the survey further highlights several potential problems for upcoming research and provides future directions to address the issues of next generation wireless networks.

INDEX TERMS Machine learning, handover, self-optimization, mobility robustness optimization, handover margin, time-to-trigger, heterogeneous networks, 5G network.

I. INTRODUCTION

The fifth generation (5G) network is considered as a key enabler in communication and information industries. High mobile traffic demands to support several services and applications are present [1], [2]. Ericsson predicts that there will be 4.4 billion 5G subscriptions by 2027. Rising mobile traffic demands must be efficiently met [3]. The increasing number of 5G subscriptions will prompt mobile operators to deploy ultra-dense small base stations (SBSs) to accommodate

The associate editor coordinating the review of this manuscript and approving it for publication was Jie Gao.

sufficient data rates for subscribers [4], [5], [6]. However, the deployment of ultra-dense SBSs will cause several mobility issues that may degrade network performance, such as radio link failure (RLF) and handover ping-pong (HOPP) [7], [8]. The user equipment (UE) requires suitable handover (HO) strategies to maintain stable and reliable radio communication links [9].

HO is a vital component of future cellular networks and necessitates proper setting since it has a direct impact on the quality of service (QoS). HO is defined as the process of handing over the radio communication link from the serving base station (BS) to the target BS when the UE's received signal from the serving BS drops below the threshold level. The HO procedure will be more complicated in ultra-dense SBSs deployments which require efficient HO triggering algorithms to achieve optimal HO settings with minimal human intervention [10], [11]. Future cellular network generations (5G networks and beyond) will require advanced self-optimization techniques to avoid network degradation [12].

Self-optimization is a key aspect of the self-organization network (SON). An automatic adjustment of HO parameters is performed to maintain connection quality during HOs [13]. The SON consists of two main components: radio frequency and radio resource management (RRM). The self-optimization falls down on RRM which also consists of two functions: mobility robustness optimization (MRO) and load balancing optimization (LBO) [14]. MRO manages HO issues according to UE movements, while LBO focuses on traffic load balancing [15]. The MRO basically auto-tunes HCPs based on the network status to control irregular HO triggering [16], [17]. MRO functions can be achieved by preserving the connection quality and utilizing network resources. This leads to lower HO failure (HOF), RLF, and HOPP while maintaining seamless communication [18].

The working procedure of the MRO function begins with controlling the input data according to the operator's targets and objectives. The MRO algorithm applied will be activated to analyse the data. If the outcomes satisfy the targets and objectives, one time MRO procedure ends. Otherwise, a corrective action will be applied for a better system status. If the target is not met after a corrective action, a fall back is required to reverse the system to the previous status otherwise, the system finalize one optimization step and starts controlling the data for the next optimization steps. However, the HO procedure has been introduced in the third-generation partnership project (3GPP), TS 28.627 version 15.0.0 release 15, [19].

In recent years, machine learning (ML) techniques have been considered as potential solutions for several MRO functions. These techniques enhance HO management by optimizing HO control parameters (HCPs), HO margin (HOM), and time-to-trigger (TTT). ML optimizes HCPs by learning, automatically extracting knowledge, and predicting an effective scenario. ML also applies statistical techniques to enhance the ML process without being explicitly programmed [20]. Therefore, ML techniques are suitable for solving various HO self-optimization issues in heterogeneous networks (HetNets) [17].

The common types of ML have been implemented to optimize the HCPs of MRO functions, such as the supervised ML [21], [22], [23], [24], [25], [26], [27], unsupervised ML [28], and reinforcement learning [14], [29], [30], [31], [32], [33], [34], [35], [36], [37], [38], [39], [40], [41], [42]. Several ML techniques under each type have been addressed as a solution method. The supervised techniques include neural networks multilayer perceptron [23], [24], neural networks based on gated recurrent units (GRU) [21], rectified linear unit with SoftMax function [26], and recurrent neural network based on GRU and long short-term-memory (LSTM) [27]. All these techniques implemented with different scenarios, HCPs, and key performance indicators (KPIs). Article [21] optimized the offset of MRO and LBO in 5G HetNets using the traffic load of the BSs as the KPI while in [22], cell individual offset (CIO) and HOM were optimized by considering the SINR in a macro BS environment. In [23], [24], and [26], the authors assessed the HCPs of the MRO function (TTT and HOM). Each study implemented different scenarios, methodologies, and KPIs. Ref. [23] examined several KPIs, such as the HOF, HOPP, and unnecessary HOs. Therefore, previous studies had analyzed the performance of HCPs in various deployment scenarios using several KPIs: the HOF, RLF, HOPP, signal-to-interference-plus-noise-ratio (SINR), throughput, handover probability (HOP), cell dropping ratio (CDR), and interruption time (IT). These studies are extensively examined in Section IV.

To the best of our knowledge, article [28] is the only research that applied unsupervised learning (K-means clustering) to investigate TTT in MRO and to balance the traffic load of the serving BS using in-building system scenarios in long-term evolution (LTE) network.

Several reinforcement learning techniques have been applied to achieve optimal HCP settings. The fuzzy Q-learning technique was used throughout numerous works [14], [29], [30], [33]. The research of [31],[32], [35], [38], [39], and [40] presented a Q-learning technique to acquire optimal HCP settings. The Q-learning technique was integrated with other methods such as Q-learning and Analytic hierarchy process technique for order of preference by similarity to ideal solution (AHP-TOPSIS) [34], deep Q-learning [42]. However, these reinforcement learning techniques have been deployed over a several deployment scenarios and different KPIs. Hence, different achievements can be seen from each approach. For instance, article [14] optimized the TTT and HOM using RLF and HOPP as a KPIs in LTE network while,[29] used HOF, CDR and HOF for optimizing the TTT and HOM. Moreover, HetNet deployment scenario is applied in [30] using HOR and CDR based on received signal reference power (RSRP). Besides, HOM and traffic load are optimized using HOR, CBR, and CDR as the performance indicators. These reinforcement learning methods optimize HO parameters without the need for dataset training.

Section IV deeply discussed all previous reinforcement studies up to now.

Most HO triggering algorithms deployed in fourth generation (4G) cellular networks are inefficient for 5G cellular network application due to different specifications and requirements. Existing HO triggering algorithms still require further assessments to achieve optimum HO solution, especially in 5G networks. Further evaluations should be based on the current specification releases in 3GPP. This survey mainly focuses on the HO self-optimization network of MRO based on ML algorithms. The contributions of this survey are as follows:

- To the best of the authors' knowledge, no review papers have highlighted or discussed MRO functions using ML algorithms.
- The MRO challenges including intra-system and inter-system mobility are discussed.
- The summarized state-of-the-art ML algorithms can assist researchers in future investigations since each algorithm includes deployment scenario, ML type, methodology used, criteria, HCPs, KPIs, simulators, and achievements.
- This comprehensive survey investigates how ML algorithms can achieve optimal HO settings by addressing the common types of ML and the technique used from each type.
- Several types of ML (i.e., supervised, unsupervised, and reinforced learning) used in MRO functions are discussed. State-of-the-art algorithms related to MRO functions that apply ML as a solution are symmetrically organized from the literature based on the year of publication and the types of learning.
- Velocity-aware and network topologies for MRO functions are addressed since it has a direct impact on system performance.
- This survey presents several challenges and potential directions in future wireless network generations (5G and beyond).

The remainder of this paper is organized as follows: Section II discusses the motivations of HO self-optimization based on ML techniques. Section III highlights several issues of the MRO function. Section IV provides the related studies. Enhancing MRO functions for future networks are provided in Section V. Section VI presents the numerous ML algorithms available. Section VII examines the various challenges and future directions. Section VIII concludes this paper.

II. MOTIVATIONS OF MACHINE LEARNING IN MRO FUNCTIONS

Wireless communication is one of many fields that use ML techniques to facilitate network complexity and improve network performance and accuracy. Due to various limitations of traditional algorithm applications, ML techniques play a crucial role in mitigating such limitations by addressing network complexity, lowing expenditures, and obtaining optimal HO self-optimization functions [43], [44]. Several motivations for employing ML algorithms have been addressed in the area of HO self-optimizations.

A. REDUCING OPEX AND CAPEX

In the early generations of mobile networks, such as the second (2G) and third (3G) generations, HO parameters were manually optimized. This negatively affected system performance and accuracy. In recent years, assigning fixed HCP values has become critical in mobile networks since the number of connected devices are dramatically increasing. High mobility users in deployed ultra-dense SBSs will be addressed in future mobile HetNets, as shown in Fig. 1. The figure presents the cellular networks from 1G to 6G, the requirements (such as peak data rate, latency, spectral efficiency, etc.), and the technologies used or will be used in future. Moreover, Fig. 1 shows the mobility of 5G and 5G mobile communication networks which can reach greater than 500 km/hr which will subsequently increases the ratio of HOPP and RLF. In addition, it should be noted that applying manual settings for high mobility users in dense HetNets will negatively affect system operators in terms of OPEX and CAPEX, further influencing network performance. Time consumption is another consequence, leading to increased operational costs and lower revenue [45].

B. REDUCING NETWORK COMPLEXITY

The contradictions found between the objectives of HO parameters and dynamic environments are two critical challenges when optimizing HO parameters. However, ML can interact with dynamic environments without requiring any previous data. ML algorithms can remarkably handle vast amounts of optimization parameters compared to conventional interpolation techniques. ML can learn, model, and map out functions that cannot be mathematically interpreted [46].

C. ACHIEVING OPTIMALITY DURIN HANDOVER

The goal of the current research is to achieve optimum HO setting in HO self-optimization networks. ML techniques have significantly contributed towards obtaining ideal HO settings by self-optimizing HCPs, thereby enhancing network performance. Reinforcement learning (i.e., Q-learning) is an ML technique used throughout various studies to self-optimize HCPs. It does not require data and can be implemented in dynamic environments.

III. MOBILITY ROBUSTNESS OPTIMIZATION CHALLENGES

TTT and HOM are considered significant HCPs in MRO. The optimization algorithm usually measures KPIs to achieve the best setting of HCP values, as shown in Tables 2, 3. The evaluation of KPIs varies from one study to the next, subsequently leading to significant differences in performance and accuracy. The contradiction between HCPs always requires further assessments to achieve efficient HO self-optimization

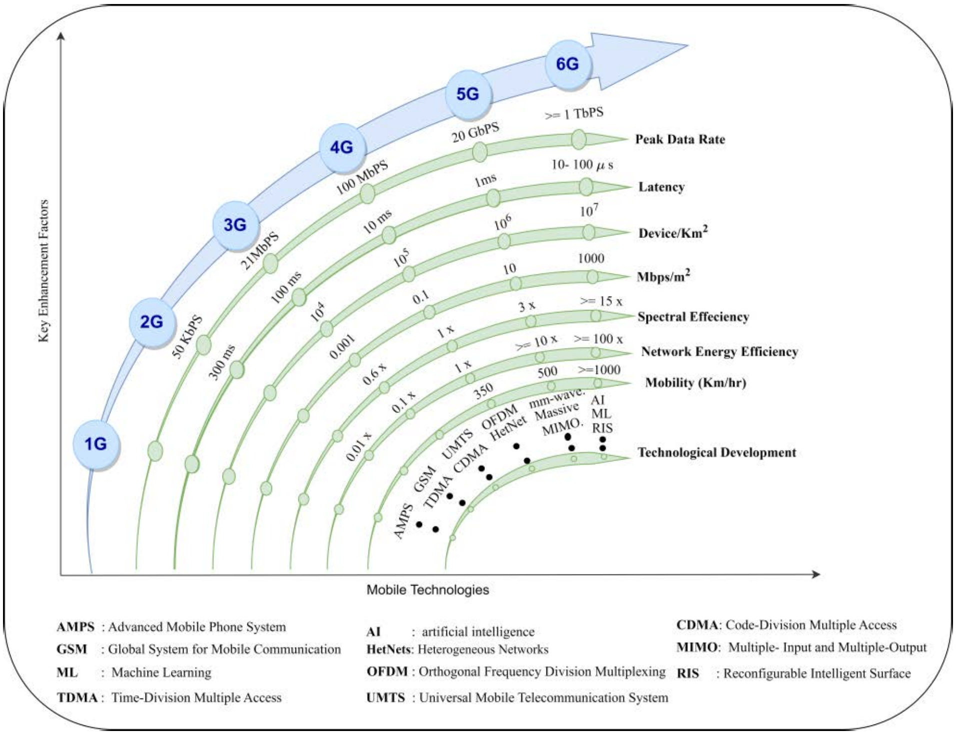

FIGURE 1. Characteristics of mobile generations.

algorithms [47]. For instance, setting the HOM value too low will increase HO probabilities too early, which will subsequently lead to HOPP. On the other hand, setting the HOM value too high will increase the HO probability too late, which will increase the RLF ratio [33], [48], [49]. The RLF requires a decrease in HOM, while HOPP requires an increase inHOM [50]. Table 1 illustrates the suboptimal optimizations of HCPs and their consequences on system performance. The main objective of MRO is to auto-tune HCPs to achieve ideal HO triggering based on the detection and correction of mobility issues, as defined in the following:

A. TOO LATE HO

The timing of HO is very critical. If HO occurs early or late, different KPIs are triggered. Increasing HCP settings leads to too late HO which causes high RLF, thereby resulting in high IT and degradation in the UE's throughput [34]. The RLF occurs when the SINR of the UE stays under the acceptable level where the connection quality is disrupted [19], [51]. The UE reports the RLF to the network to investigate connection failures. These reports are either fetched by the network or link failure will be reported [51], [52], [53]. The RLF usually occurs in both intra-system and inter-system mobility as follows:

1) INTRA-SYSTEM TOO LATE HO

The RLF in the intra-system is detected only between BSs that have the same systems, for instance, switching the HO from next generation-radio access network (NG-RAN) serving BS A to NG-RAN target BS B. In intra-system too late HO, the RLF occurs before the successful initiation of the HO procedure to the target BS that has the same system mobility.

TABLE 1. Suboptimal settings of MRO parameters.

MRO issues	TTT value	HOM value	Affected KPI levels
Too late HO	High	High	High RLF
To early HO	Low	Low	High HOPP
HO to wrong cell	Inappropriate	Inappropriate	High RLF or High HOPP

2) INTER-SYSTEM TOO LATE HO

The RLF in inter-system mobility is detected between BSs that have different systems, for example, switching HO from an evolved universal terrestrial radio access (E-UTRAN) serving BS to NG-RAN target BS. In inter-system too late HO, the RLF occurs before establishing successful connection to the E-UTRAN target BS. The UE stays for long periods of time in the NG-RAN serving BS.

B. TOO EARL HO

Reducing the HCP settings (TTT and HOM) leads to too early HO, as shown in Table 1. Since the execution is quickly accomplished, this leads to high ping-pong effects which causes high signaling load to the network due to unnecessary HO. HOPP occurs when the serving BS hands over the control of the UE to the target BS, then the target BS hands the control of the UE back to the previous serving BS within a predefined limited time [54]. Reducing frequent HOs will lead to the preservation of network resources, thereby enhancing system performance.

1) INTRA-SYSTEM TOO EARLY HO

In intra-system too early HO, the HOPP occurs shortly after the successful initiation of the HO procedure from the serving BS to the target BS in the same system. The UE attempts to re-establish a connection to the serving BS.

2) INTER-SYSTEM TOO EARLY HO

In two different systems, such as theNG-RAN and E-UTRAN, the HOPP in inter-system too early HO occurs shortly after a successful initiation of the HO procedure from the E-UTRAN serving BS to the NG-RAN target BS. The UE attempts to re-establish a connection to the E-UTRAN serving BS.

C. HO TO WRONG CELL

Inappropriate HCP settings lead to HO to the wrong cell which may cause degradation in system performance due to the occurrence of RLF or HOPP. In HO to the wrong cell, RLF or HOPP is conducted shortly after the successful initiation of the HO procedure from the serving BS to the target BS. The connection is re-established by the BS that is neither the target BS nor the serving BS. This connection re-establishment can be made from intra-system or inter-system HO to the wrong cell.

IV. RELATED WORKS

Several research that applied different approaches to HO self-optimization (i.e., MRO) are present. Our study [55] comprehensively addressed several non-ML methods applied to the MRO function for optimal HCP settings such as RSRP-based [56], [57], [58], [59], [60], [61], [62], [63], [64], [65], weight function [48], [66],[67], [68], fuzzy logic controller (FLC) [69], [70], [71], [72], [73], speed scenarios [74], [75], [76], [77], [78], [79], [80], UE speed with traffic load [70], dwelling time [81], and combined techniques (i.e., weighted FLC [82], Fuzzy AHP [83], and fuzzy TOPSIS [84]). have been applied in MRO. Therefore, this survey is limited to MRO that uses ML techniques to extensively examine the topic in a clear and concise manner. Several approaches with different ML techniques have been addressed throughout the literature.

A. MRO USING SUPERVISED LEARNING

The supervised technique has been applied as a solution in various studies related to HO self-optimization. Each of the following research is unique in terms of the deployed scenario, criteria, HCPs, KPIs, and simulation tools applied. This has subsequently led to different accuracies using other approaches, as shown in Table 2. The following studies mainly address the MRO function that uses supervised learning, such as in [21], [22], [23], [24], [25], [26], and [27]. Table 2 is organized according to the sequence of research in terms of criteria, HCPs, KPIs, and performance achievement.

The data-driven HO optimization (DDHO) approach was proposed to minimize KPIs (i.e., too late HO, too early HO, HO to wrong cell, unnecessary HO, and HOPP) [23]. Multilayer perceptron was also used as a solution for estimating these KPIs. However, the enhancement of KPIs only range between 15% to 20% in [21].

Kumari proposed the DDHO approach to minimize mobility issues such as HO delay, too late HO, too early HO, and HO to the wrong cell [24]. The suggested framework begins with data collection from the mobile communication network, followed by the identification of the type of mobility issue with the application of various counters. The DDHO approach then analyzes data to obtain the ratio for each mobility problem. The data is forwarded to the KPI estimation engine to optimize HCPs (TTT and HOM). Lastly, the obtained HCP values are applied to the related eNB. The results revealed an overall enhancement in mobility issues, especially when low transmission power (15 dBm) is applied.

In [21], neural network based on GRU BSs was proposed to predict the movement of UEs. A training data was created from two BSs allocated in Lviv city, Ukraine. The GRU was introduced to solve the short memory issue of recurrent neural network due to its ability to use previous knowledge of UE movements to acquire future information. The proposed model further investigated the offsets of MRO and LBO. A new coefficient was offered to determine which of the two offsets is most relevant. The LBO offset is applied when the BS is overloaded, otherwise, the MRO offset is used. 90% prediction accuracy of UE movements between BSs was achieved using the neural network. By predicting the user movement, the user traffic can be controlled which will subsequently enhance the UE's connection quality.

Due to the difficulties in handling large numbers of configurations and optimization parameters using conventional interpolation techniques, the ML framework with the heuristic technique were proposed by Shodamola et al. for successfully optimizing control parameters (CIO and HOM). This was achieved by maximizing KPIs, such as the SINR [22]. Firstly, data is generated by several simulators. Next, five ML techniques are applied (i.e., linear regression, K-nearest neighbor, extreme gradient boosting, categorical boosting, and deep neural network) to predict the behavior of SINR. Lastly, in the output of the ML techniques, heuristic search technique in the form of genetic algorithm (GA) is used to detect the optimal value of SINR. Based on the investigation addressed in [22], the best prediction performance among the five ML models was the categorical boosting model. GA was also considered as an efficient algorithm for determining an optimal solution with less iterations (i.e., 500) compared to the Burte force technique. To avoid partial optimization, the study should investigate the

TABLE 2. Optimizing MRO using supervised and unsupervised learning.

Ref.	Scenario	Mobility model	ML Type	Method	Criteria	HCPs	KPIs	Simulator	Achievements
[23]	HetNet	Manhattan grid	Supervised	Neural networks multilayer perceptron	RSRP	TTT HOM	HOF, unnecessary HOs, and HOPP	LTE-sim	The enhancement of KPIs ranges from 15% to 20% compared to the presented algorithms.
[24]	Small cells network (Femtocell)	Manhattan grid	Supervised	Neural networks multilayer perceptron	RSRP	TTT HOM	Too early HO, HO to wrong cell, and HO delay	MATLAB	The enhancement achieved for KPIs varies between 12% to 15.4%.
[21]	HetNet 5G network	Random way based on neural network prediction	Supervised	Neural networks based on GRU		Offsets of MRO and LBO	Traffic load on BS	-	90% prediction accuracy of UE movements between cells was achieved by using the neural network.
[22]	Macro BSs	-	Supervised	Supervised techniques with GA	RSRP	CIO HOM	SINR	Ray-tracing based industry grade system-level simulator	Categorical boosting model is the best ML model presented.
[26]	5G ultra - dense urban network	Random Walk for indoor and Manhattan for outdoor	Supervised	Rectified linear unit and SoftMax function	SINR SINR change	TTT HOM	RLF and HOPP	-	The RLF and HOPP were reduced compared to other presented algorithms.
[27]	5G ultra-dense network	Random way point	Supervised	Recurrent neural network based on GRU and LSTM		Offsets of both MRO and LBO	Loads at BS	-	Accuracy in determining the prioritized offsets to be used in the network.
[28]	LTE in-building BSs underlying macro BSs	Random way point	Unsupervised	K-means clustering algorithm and data mining	RSRP	TTT load	Load levels at the BS and RF conditions	-	Enhanced spectral efficiency at the BS edge

optimal TTT since it is one of the most essential parameters in MRO.

Deploying dense SBSs that underly traditional macro BSs will lead to a variation in the SINR during HOs. This will subsequently increase the ratio of RLF and HOPP. Huang et al. [26] proposed a supervised learning with deep neural network according to the SINR and SINR change (used as inputs) to reduce RLF and HOPP. Based on the UE's experience, the measurement data was categorized as two classes: the RLF class and the HOPP class. After data classification, supervised learning was used to train the deep neural network which consists of one input layer, two hidden layers, and one output layer. Rectified linear unit and the SoftMax function were used in the hidden layer and output layer, respectively. The objective of the SoftMax function is to convert the weighted sum of all values taken from the rectified linear unit into probabilities for each class. If the probability of RLF is higher than the probability of HOPP, the UE experiences RLF and vice versa. The deployment scenario was based on 3GPP 5G dense urban network [2]. In this study, 27 macro BSs were deployed in the environment, and 4-8 micro BSs were implemented under each macro BS.

Future wireless communication networks (5G and beyond) will face rapid changes and unplanned deployment of massive SBSs, which will subsequently affect user satisfaction. Recurrent neural network based on GRU and LSTM BS have been proposed to maintain the previous information of the UE and to understand the current user mobility [27]. LSTM has three filters that can eliminate information from the cell state. The GRU, which includes an update and reset layer, was also addressed in this study to solve the gradient disappearance issue. The update layer was employed to filter past data and determine how much data is approved for future use, while the reset layer deletes the unapproved data. The GRU requires less resources and less training data than LSTM in terms of cell-based architecture. Therefore, the data can be trained a little faster compared to LSTM. This study investigated the offsets of MRO and LBO to determine the most relevant offset to be used at each situation. The results revealed that the traffic prediction accuracy reaches 90%.

B. MRO USING UNSUPERVISED LEARNING

To the best of the authors' knowledge, [28] is the only study that investigated TTT in MRO function using unsupervised learning (K-means clustering algorithm). Table 2 presents the examined parameters of this study.

Castro-Hernandez and Paranjape [28] have proposed a novel approach based on ML and data mining techniques to discover and learn the radio frequency conditions. The authors further suggested a novel method to adjust HO parameters according to the acquired data of evolved nodes B (eNBs) using the TTT parameter. They also offered a load balancing approach for users in connected mode. The suggested solutions were conducted to solve the HOF caused by late or early HOs as well as unnecessary HOs. ML (K-means clustering algorithm) and data mining techniques were proposed to allow the in-building system to autonomously learn and identify characteristic patterns in the signal strength received from users as they approach the cell-edge. Next, optimal HO parameters were applied for each case. Experimental data collected from two fully operational LTE in-building systems were deployed in the two buildings of the university campus. One building was considered as a hotspot area where the food court and student union offices are located. The operating frequencies of the LTE macro BS were 2.1 and 2.6 GHz. The approach provided an average data rate gain between 25% and 65%. The data rate gain can also reach a value close to 150% for certain loading conditions. The spectral efficiency at the BS edge was further enhanced as well.

C. MRO USING REINFORCEMENT LEARNING

Most MRO studies have applied reinforcement learning, mainly Q-learning, as a solution for obtaining the optimal triggering value during HO. Table 3 presents the related studies.

Decreasing revenue and increasing costs have become a concern for network operators. Self-optimizing HO parameters may reduce operational expenditure since it decreases human intervention when adjustments are needed. The fuzzy Q-learning-based MRO approach has been suggested for HO parameter adjustments [29]. The proposed approach includes the fuzzy inference system, heuristic exploration/exploitation policy, and Q-learning components. Several KPI parameters (CDR, HOF ratio, and HOPP ratio) were also evaluated [29]. This study distinguished between services that can tolerate certain connection interruptions (non-real time services such as videos) and services that cannot tolerate any connection interruptions with time (such as voice services).

Fuzzy Q-learning algorithm was also suggested to optimize HOM and TTT in HetNets [30]. The system was evaluated based on two KPIs (the CDR and HO rate) using A3 triggering event. The main objective of the study is to balance the signaling traffic created by HOs with CDR. The KPIs were used as inputs to the network, also considered as the system state in the Q-learning algorithm. To implement the algorithm, the HOM-change was represented as the action and considered as the output of the system. Random actions were also chosen by the system with FLC. The UE's speed and TTT were 10 km/hr and 200 ms, respectively. In [30], TTT and HOM must be automatically tuned for increased system accuracy.

In [31], the Q-learning method was proposed to advance SON functions (MRO, LBO, coverage, and inter-cell interference coordination (ICIO)) into cognitive cellular network functions. It was noted that MRO and LBO are the two most suitable functions for Q-learning due to their similar states in BSs. The proposed algorithm investigated the sensitivity of HCPs when changes occur in the UE's velocity. In relation to the MRO function, Q-learning based MRO solution has the ability to learn the setting of TTT and HOM.

Maximizing the throughput and minimizing the number of HOs are essential for achieving optimal triggering points. Abdelmohsen et al[32] proposed a Q-learning optimization algorithm to maximize the system throughput, minimize the total number of HOs, and reduce the system delay over three different UE speed scenarios (10 km/hr, 60 km/hr, and 160 km/hr). System delay is defined as the time duration from the arrival time of the queuing packet at the eNB buffer to the current time. Q-learning was used to determine the optimum triggering points of HOM and TTT. The proposed algorithm exhibited system performance enhancements in terms of throughput (15% increment), HOs (30% reduction), and delay as compared to the enhanced mobility state estimation algorithm mentioned in [80].

Hegazy et al. proposed a fuzzy Q-learning algorithm to self-optimize two conflicting problems: RLFs and ping-pongs [14]. The contradiction indicates that the former requires decreased HOM to mitigate late HO, while the latter requires increased HOM. The algorithm was presented according to the categorization of users, such as the speed and traffic load of eNBs. These categories are as follows: slow speed real time users, slow speed non-real time users, high-speed real time users, and high-speed non-real time users. Various HOM and TTT with user categorizations were analyzed by assessing their changing effects on the system. The proposed algorithm revealed an increment of 5.4% in the total HO rate and 6.2% for the compared algorithm in the literature (i.e., fuzzy Q-learning).

A joint optimization algorithm between load balancing and MRO based on the fuzzy system and Q-learning mechanism was proposed in [33]. The fuzzy system adjusts HO parameters to enhance system performance, which is then optimized by the Q-learning algorithm to select the most suitable action from the load balancing and MRO. The fuzzy system also makes decisions based on the previous actions measured by the KPIs. The proposed algorithm was presented to solve the conflict between the two SON entities (LBO and MRO). This contradiction requires an additional entity, such as a coordinator, to manage the discrepancy and reduce system complexity. However, the proposed algorithm demonstrated the effective enhancement in traffic congestion mitigation and HO reductions. TTT should be applied as an additional

TABLE 3. Optimizing the HCPs of MRO using reinforcement learning.

Ref.	Scenario	Mobility model	Method	Criteria	HCPs	KPIs	Simulator	Achievements
[29]	LTE network	Fixed forward direction	Fuzzy Q-learning	RSRP	HOM TTT	HOF, HOPP, and CDR	LTE system level radio network	Improvements in applied KPIs
[30]	HetNet	Random way point	Fuzzy Q-learning	RSRP	TTT HOM	HOR and CDR	LTE system level	Significant reductions in HOR while maintaining CDR at an acceptable limit
[31]	Cognitive cellular network	Random walk	Q-learning	RSRP	TTT and HOM are used for MRO function. CIO is used for LBO function. Antenna tilt is used for CCO function. Tx power is used for ICIC function.	HOPP and RLF for MRO function, load for LBO function, spectral efficiency for CCO function, and mean throughput for ICIC function	C++ LTE system level	Q-learning approach has the ability to learn the setting of HO parameters for enhancing SON solutions.
[32]	LTE network	Random way point	Q-learning	RSRP	HOM TTT	Throughput and number of HOs		Throughput was enhanced by 15%. The number of HOs was further reduced by up to 30%.
[14]	LTE network	Random way point	Fuzzy Q-learning	RSRP	HOM TTT	RLF and HOPP	LTE-sim	Decreases HOPP while maintaining RLF at an acceptable limit
[33]	LTE network	Random way point	Fuzzy Q-learning	RSRP	HOM Load	HOR, CBR, and CDR	Dynamic system level	Traffic congestions and HOs are mitigated. Joint optimization between LBO and MRO reduced the complexity of SON functionalities.
[34]	LTE-A network	Random way point	AHP-TOPSIS and Q-learning	RSRP, RSRQ, SINR, and load on BS	TTT HOM	HOF rate and HOPP	MATLAB	Optimal selection of eNB and triggering values, respectively
[38]	HetNet	Random way point	Q-learning	RSRP	TTT	Throughput	MATLAB	25% improvement in the average throughput
[39]	LTE network	Random way point with constant speed	Q-learning	RSRP	TTT HOM	HOPP RLF	MATLAB	QoE-aware algorithm shows 0.2 mean opinion score higher than Q-MRO algorithm.
[40]	Small cell Network	Mahattan grid and Random way point	Q-learning	RSRP	TTT HOM CIO	HOF HOPP	-	416 % was the rate satisfaction of the proposed algorithm compared to the algorithms [57] and [31].
[41]	5G network	Constant velocity	State–action–reward–state–action	RSRP	TTT HOM	HOF Latency throughput	NS-3	Significant reductions in HOF and latency with improvement in throughput compared to [85] and [86].
[42]	LTE ultra-dense small BSs	Random way point	TOPSIS deep Q-learning	RSRP SINR Traffic load	TTT HOM	HOF HOPP throughput	-	Decreases in HOF and HOPP as well as enhancements in throughput over the algorithms [87], [88], and [34].

parameter since it is the most significant control parameter in the MRO function.

The optimal selection of target eNBs and accurate triggering points require further optimizations to reduce the HOF and HOPP effects. To select an ideal target eNB, several HO parameters with precise settings are necessary.

These parameters include the received signal reference quality (RSRQ), current load on eNB, uplink SINR, as well as the moving direction and location of UEs. Goyal et al. proposed the AHP-TOPSIS method for the optimal selection of the target eNB [34]. To obtain optimum eNB, appropriate ranking of each UE should be provided by the AHP-TOPSIS method at the eNBs. The highest UE rank will be re-attached to its eNB and considered as optimal. The ranking criterion of the UE is based on the running applications of the UEs (delay sensitive and speed sensitive applications) or high definition videos. Priority is given to delay sensitivity applications so as to avoid latency issues. After selecting the best target eNB, the Q-learning approach is proposed for the proper setting of TTT and HOM. The coverage size and time duration required by the UE in the area are expected to obtain the optimum triggering value. For the best triggering points, Q-learning was used as the final stage before HO execution. The reductions of the HOF rate and HOPP were 28% and 25% in the conventional method, and 35% and 33% for the fuzzy multiple-criteria cell selection scheme.

In [38], HO was considered for visible light communication (VLC). In this paper, Shao et al. proposed a comprehensive and flexible framework that controls self-optimization at the centralized coordinator based on the Q-learning approach. This centralized coordinator is located at LTE eNB to control the HO parameters of all VLC access points under the LTE eNB coverage. In previous works, non-comprehensive investigations were conducted to solve the problem of access point-user association of heterogeneous radio-optical networks. However, previous research had either focused on quasi-static network selection or only considered vertical HO dwell time from optical to radio. The assumption of the quasi-static method causes outdated decisions for high mobile scenarios since it ignores the significance of the dwell time vertical HO from radio to optical, and only focuses on optical to radio HO. The optimum signal quality of these analyses are unsatisfactory due to frequent disconnections. Designed Q-learning based algorithm maximizes the average throughput by learning the best sequence of TTTs. It has been noted that the average throughput of small TTT space will not decrease to a very low value (below 90 Mbps) during the training process of online Q-table. The outcomes revealed that 25% improvement in average throughput was achieved by the proposed Q-learning based algorithm when compared to the fixed TTT scheme.

Customer expectations are increased as a result of the improvement of the network capabilities. Operators have been pushed by these developments to re-focus their attention from network performance to end user opinion (i.e., quality of experience (QoE)). For this reason, María et al. proposed QoE-aware Q-learning algorithm for the MRO function to reduce the ratio of HOPP and RLF [39]. Several facilities were examined such as video streaming, web browsing, file download service, and voice over internet protocol. The study was deployed over LTE network with constant mobile speed scenarios (i.e., 30 km/hr and 70 km/hr). Moreover, random way point was applied as a mobility model. The main objective of this study is to find the optimal setting value for the TTT and HOM. However, Q-MRO and QoE-aware algorithms were addressed. The first experiment has been optimized without considering QoE-edges. Hence, the HO performance is enhanced at the cost of degrading the QoE of the users at the cell edges by 0.2 mean opinion score. The measurement scale of the QoE (i.e., mean opinion score) ranges from 1 (bad) to 5 (excellent).

In [40], a distributed reinforcement learning was proposed to adapt the UE mobility along with proposing ML-based algorithm (i.e., transfer learning based algorithm) for a dynamic network topology adaption. The main objective of the proposed algorithm is to optimize the HOM, TTT and CIO over a dynamic small BSs to minimize the ratio of the HOF and HOPP. Furthermore, two steps were considered for the HO optimization. First step is to achieve the prior knowledge as a coarse optimization while, in the second step, the knowledge have been utilized using reinforcement learning to auto-tunes the HCPs (i.e., HOM, TTT, and CIO). In addition, the study has applied a random mobility model with two mobile speed scenarios (i.e., 30 km/hr and 70 km/hr) over a simulation environment of 12 small BSs. In addition, Manhattan grid mobility model is used at speed of 5 km/hr and 30 km/hr. The proposed algorithm's adaptation time was 4.17 % shorter than the comparative machine–based algorithm. Furthermore, 416 % was the enhancement in the satisfaction rate at UE's speed of 5 km/hr compared to MRO algorithm based on classification [57], and Q-learning-based MRO [31]. In addition, the adaption time reduction at speed of 5 km/hr was 4.17 minutes compare to 100 minutes and 79.17 minutes in [57] and [31], respectively.

Very high mobile speed scenarios requires a steady connection during the transition of UE's from one BS to another. Moreover, high number of connected devices in ultra-dense networks need a proper HO algorithm to auto-tunes the TTT and HOM. Therefore, Raja et al. proposed learning-based intelligent mobility management mechanism to self-optimize the TTT and HOM based on HOF, latency, and throughput [41]. Kalman filter has been used to predict the RSRP of the serving and target BSs. Consequently, the target BS will be chosen by state-action-reward-state-action-based reinforcement learning. Then, ϵ-greedy policy is used for auto-tuning the TTT and HOM. Furthermore, a prototype for learning-based intelligent mobility management has been created using the network simulator (NS-3) over 5G deployment scenario. In addition, several mobile speed scenarios (i.e., 50 km/hr, 100 km/hr, 150 km/hr, 200 km/hr, 250 km/hr, 300 km/hr, 350 km/hr) were applied in [41]. However, the results show that the average throughput of the proposed mechanism is 19 % and 68 % higher than the mechanisms applied in the literature which are the reliable extreme mobility [85] and contextual multi-armed bandit [86], respectively. Besides, the applied mechanism shows a reduction by 28 % and 42 % in packet loss rate compared to [85] and [86], respectively. During high mobile speed scenario (i.e., 350 km/hr), the HOF rate of the presented mechanism shows a 2 % and 44 % reduction over [85] and [86], respectively.

In [42], a software defined network-enabled based on TOPSIS and deep recurrent Q-network HO strategy is applied to automatically adjust the TTT and HOM. TOPSIS used to preselect the target BS based on the RSRP, SINR, and traffic load. Then, the software defined network controller auto-tunes the TTT and HOM using deep reinforcement learning-based according to the selected target BS. In addition, The KPIs used in [42] include HOF, HOPP, and throughput to show how well the configuration of TTT and HOM is. Besides, random waypoint mobility was applied over LTE ultra-dense small BSs. However, the proposed algorithm shows an improvement in HOF by 55.93%, 45.17%, and 38.13% compare to traditional HO algorithm [87], upper confidence bound algorithm [88], and Q-learning algorithm [34], respectively. Furthermore, HOPPs were reduced by 66.85%, 55.03%, and 43.5% compared to [87], [88], and [34], respectively. In addition, the proposed algorithm shows increases in throughput by 55.48%, 43.02%, and 24.26% compared to the other algorithms presented.

Several ML types using different approaches have been applied in the HO self-optimization field where optimum HO settings with minimal human intervention are required. The proposed methods significantly contribute towards reducing system complexity and controlling the discrepancies between HO parameter objectives. Although all common ML types (supervised, unsupervised, and reinforcement learning) have been used, further assessments are needed to achieve an efficient algorithm that can obtain optimal values for HCPs (TTT and HOM). The anticipated release of the 3GPP specifications modeled for 5G systems are still required for further research. With the advancement of transportation systems, speed scenarios can reach up to 500 km/hr. Preserving connection quality is a critical issue in mobility management.

V. ENHANCING MOBILITY ROBUSTNESS OPTIMIZATION FUNCTIONS FOR FUTURE NETWORKS

Several studies have been addressed for achieving the optimal triggering value for the HCPs in MRO functions. However, these studies have optimized the HCPs using various algorithms with several deployment scenarios, KPIs, and different mobile speed scenarios.

A. VELOCITY-AWARE AND TOPOLOGIES IN FUTURE MOBILE NETWORK

As for homogeneous networks, numerous efforts have been made for auto-tuning the HCPs based on mobility state estimation by counting the number of HOs according to the UE's speed. However, at HetNet environments where the random deployments of the different cell sizes are used, self-optimizing HCPs still a complex task compared to those in homogeneous.

High mobility scenarios in ultra-dense HetNets may create a large number of frequent HOs which will subsequently increase the system mobility issues (i.e., too late HO, too early HO, and HO to wrong cell). Therefore, MRO function aims to detect and correct these mobility issues through a proper optimization settings of the TTT and HOM. Moreover, drones' usage has increased rapidly nowadays with high capabilities to serve in future mobile network and offering a numerous solutions in several environments. But, drones' velocity-aware are required since high speed may lead to increasing in HO rates, HOPP, RLF. Therefore, several MRO studies based on UE's speed have been extensively addressed in our work [55].

Based on the algorithms addressed in this study, HCPs of the MRO were optimized under a several network topologies. These topologies includes 5G network [8], [41], [48], [89], HetNet [23], [30], [38], [56], [59], [60], [71], [75], [82], LTE-network [14], [29], [32], [33], [34], [39], [70], [74], [76], [77]. Moreover, several network topologies are addressed in Tables 2, 3. However, these topologies have a direct impact on system performance especially when high-speed scenarios are applied. Nowadays, 5G network and beyond has the ability to support high-speed scenarios up to 500 km/hr as shown in Fig. 1. The case will be more critical when implementing a small dense millimeter waves (mm-waves). Hence, large number of frequent HOs will occur which may increase the ratio of unnecessary HOs, RLF and HOPP. Therefore, further investigations are needed to came out with the effective algorithm that is suitable with the requirements and specifications of the future mobile HetNets.

B. MOBILITY MODELS FOR MRO FUNCTION

This subsection presents the mobility models used in previous MRO with ML studies presented in the literature until now. Manhattan mobility model is used in [23] and [24] where the user is moving either in vertical or horizontal direction. In [21] the user is moving randomly based on the neural network predictions. The authors in [26] addressed two mobility models: random walk mobility model for the indoor scenarios at speeds up to 10 km/hr, and Manhattan mobility model which used for outdoor scenarios at speeds between 30 km/hr and 60 km/hr. Random waypoint mobility is applied in [14], [27], [28], [30], [32], [33], [34], [38], and [42]. The users moving in fixed straight forward direction in [29]. Article [31] applied random walk mobility model. Manhattan grid mobility model and random way point mobility model are presented in [40], the random way point mobility model used in pedestrian environment at user speed of 5 km/hr. Constant velocity mobility model is introduced in [41].

VI. MACHINE LEARNING TECHNIQUES FOR MOBILITY ROBUSTNESS OPTIMIZATION FUNCTIONS

In recent years, ML has proven to be significant in achieving ideal HO triggering points by self-optimizing HO parameters in a dynamic environment. However, 5G wireless networks vary from ML in terms of their individual research fields. Wireless networks combined with ML can learn and extract data when interacting within a dynamic environment. Enabling ML in future wireless networks (5G and beyond) will increase the capabilities of user mobility estimations, HO self-optimization, and decision-making, thereby creating cost effective networks. Fig. 2 presents the integration of ML with a wireless communication system as a method for solving issues related to MRO functions. Ultra-dense HetNets with different speed scenarios and several deployed environments as well as the traffic loads of the serving and the target BS are addressed in Fig. 2. Dataset was collected from different BSs that belong to various radio access technologies to model the potential application. As shown in Fig. 2, with introducing the ML techniques, the complexity of the future mobile communication systems can be reduced through predicting the target BS based on the dataset collected. Moreover, deep learning has been introduced in Fig. 2 since it has the capabilities for eliminating undesired datasets which will subsequently reduce the storage issues [27]. Nowadays, by considering a deep learning, the ML community achieved a huge leap toward the success of many ML tasks [43].

This section extensively examines the different ML types for HO self-optimization. The survey focuses on the optimization of control parameters in the MRO function. Unlike traditional programing, ML depends on learning from the input data to predict the desired output. Based on the method of learning, ML has been classified into three categories: supervised ML, unsupervised ML, and reinforcement learning. The following sections further explain the ML algorithms proposed by previous studies in MRO functions.

A. SUPERVISED ML FOR MRO

Supervised learning is considered as one of the main solutions that can efficiently solve MRO in future mobile networks. In supervised ML, a labeled input data is fed to the network to connect to a labeled output data. However, when the labeled data is continuous, it is considered as a regression problem. The main goal of supervised ML is to obtain an effective algorithm that can obtain accurate predictions of new data based on the relationship of the labeled input and output data, as shown in Fig. 3. In addition, Fig. 3 represents an overview of how the data are collected from the wireless networks. Due to the confidentiality of revealing the wireless communication datasets, synthetic data including measurement reports, such as RSRP, traffic load, SINR, and mobile speed scenarios, are generated for optimizing the HCPs of the MRO. However, different deployment scenarios create different datasets since the measurement report's values will be different. The trained ML algorithms shown in Fig. 3 are addressed in Table 2 as this work is only related to MRO functions.

The formulation of supervised ML further contains a training dataset of instances x corresponding to its label y. Next, the ML algorithm a_θ (neural network, linear model, decision tree, etc.) will assign all addressed instances to labels.

$$a_\theta\,(x) \rightarrow y \tag{1}$$

The predictor quality of performance is measured by using the loss function:

$$L(y, a_\theta(x)). \tag{2}$$

The loss function can be minimized by obtaining parameter $\boldsymbol{\theta}'$, as in the following equation:

$$\boldsymbol{\theta}' \leftarrow \arg\min_{a} L(y, a_\theta(x)) \tag{3}$$

The studies addressed in [21], [22], [23], [24], [25], [26], and [27] have used supervised ML as a method for solving issues related to HO self-optimization in HetNets. The supervised ML techniques that have been used in MRO studies include linear regression, K-nearest neighbor, extreme gradient boosting, categorical boosting, deep neural network (i.e., rectified linear unit and SoftMax function), and neural network multilayer perceptron. The research of [21], [25], and [27] presented recurrent neural network techniques for HO optimization in 5G networks. The authors in [21] applied neural networks to utilize the offsets of MRO and LBO. The LBO offset is used when the serving BS is overloaded, otherwise, the MRO offset is applied. The ML framework and the heuristic technique was highlighted by [22] to optimize HCPs (HOM and CIO) by maximizing the SINR. The neural network multilayer perceptron method was employed by [23] and [24] to reduce connection failures and unnecessary HOs in MRO. These studies were conducted for various environments using different evaluated parameters. This has led to significant variations regarding their performances and accuracies.

Obtaining a training dataset become a challenging problem due to dataset protection and regulation from the communication companies. However, the supervised studies presented in the literature have generated their own synthetic dataset by using several simulators (i.e., Matlab, LTE-simulator, and ray-tracing based industry grade system-level simulator) except authors in [21] have collected their data from two BSs located in Lviv city.

B. UNSUPERVISED ML FOR MRO

Unsupervised learning techniques are key solutions for solving MRO challenges. They can contribute towards obtaining efficient algorithms in future mobile networks. In unsupervised learning, data is unlabeled. The main goal of this technique is to determine regular patterns from the training data [46], [43]. Clustering is another ML process that has proven to achieve excellent results in wireless networks when edge devices are grouped together. It can be defined as a process of combining data into similar individual units of each user [90]. Unsupervised ML (K-means clustering algorithm) was proposed by [28] to allow the in-building system to autonomously learn and identify characteristic patterns in the signal strength received from users as they approach the BS edge. The dataset in [28] was generated experimentally by deploying two LTE in- building systems in two buildings of the university campus. The operating LTE frequency applied were 2.1 and 2.6 GHz. Ref. [28] also used the MRO function to optimize TTT for system performance, as explained in Section IV.

C. REINFORCEMENT LEARNING FOR MRO

Reinforcement learning is highly effective in tackling problems related to unpredictable network environments [91]. It can obtain optimum HO triggering values by predicting future decision policies based on the feedback of previous

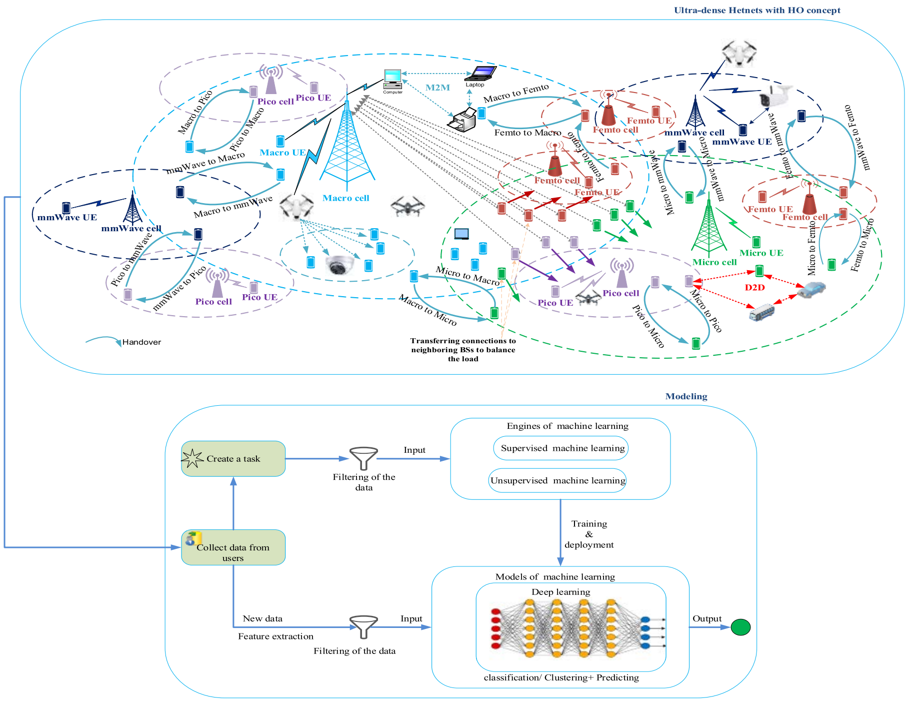

FIGURE 2. **ML for future mobile communication systems.**

decisions [92], [93]. Reinforcement learning has the ability to interact with the network environment without requiring any previous dataset or knowledge of any future changes in a dynamic environment [94]. When the agent interacts with the environment in reinforcement learning, the environment responds with either punishment or reward. The agent then optimizes its behavior based on these responses to minimize the punishments and maximize the rewards [95].

Most studies throughout the literature have highlighted reinforcement learning as a promising solution for achieving optimum HO triggering values. These studies are classified as follows:

The fuzzy Q-learning technique was addressed in [14],[29], [30], and [33]. The research of [31], [32], [35], [38], [39], [40] also presented the Q-learning technique for obtaining ideal HCP settings. Other techniques (i.e., AHP-TOPSIS, subtractive clustering, subtractive clustering with FLC, and TOPSIS deep learning) integrated with Q-learning were also addressed in [34], [36], [37], [42].

1) Q-LEARNING

Q-learning is a model-free off-policy reinforcement learning algorithm that does not require models to solve learning problems [31]. Q-learning has played a vital role in learning and improving network solutions through experience. Equation (4) represents the Q-learning technique for determining the best Q-values based on the framework process of reinforcement learning[96]:

$$Q(s_t, A_t) \leftarrow Q(s_t, A_t) + \alpha[R_{t+1} + ɣ(\max_a Q(s_{t+1}, a)) - (s_t, A_t)] \quad (4)$$

where $Q(s_t, A_t)$ is the current action-value function, $\boldsymbol{\alpha}$ is the learning rate, R_{t+1} is the expected reward at the next time step, ɣ is the discount factor, and $\max_a Q(S_{t+1,a})$ is an estimate of the ideal future action-value function at the next time step over all possible actions [97]. The Q-learning framework consists of state, action, and reward functions. The optimal policy is provided from a set of Markov decision processes [36].

The Q-learning algorithm was addressed in the HO self-optimization field in [31],[32], [35], [38], [39], and [40]. The authors in [31] proposed Q-learning to advance SON functions into cognitive cellular network functions. Self-optimization functions (MRO, LBO, CCO, and ICIO) were mapped to Q-learning. Table 3 presents the scenario, HCPs, KPIs, and simulation tool, as highlighted in article [31]. Ref. [32] proposed a Q-learning optimization algorithm to solve the issues related to HOs, throughput, and delay within the LTE network. The study objective is to determine the optimum triggering points of HOM and TTT over three different UE speed scenarios (10 km/hr, 60 km/hr, and 160 km/hr). In [35], a novel method was suggested to enhance the UE's HO based on the RSRP using Q-learning. The study was conducted to increase the RSRP average link beam gain in 5G cellular networks. The authors in [38] further suggested a framework which controls self-optimization at the centralized coordinator based on the Q-learning approach. The designed Q-learning based algorithm can maximize the average throughput by learning the optimal sequence of TTTs. It is considered as an appropriate study for managing the dynamic environment of HetNets. QoE-aware Q-learning algorithm was addressed using HOPP and RLF as a KPIs to optimize the TTT and HOM [39]. The UEs move at low speed

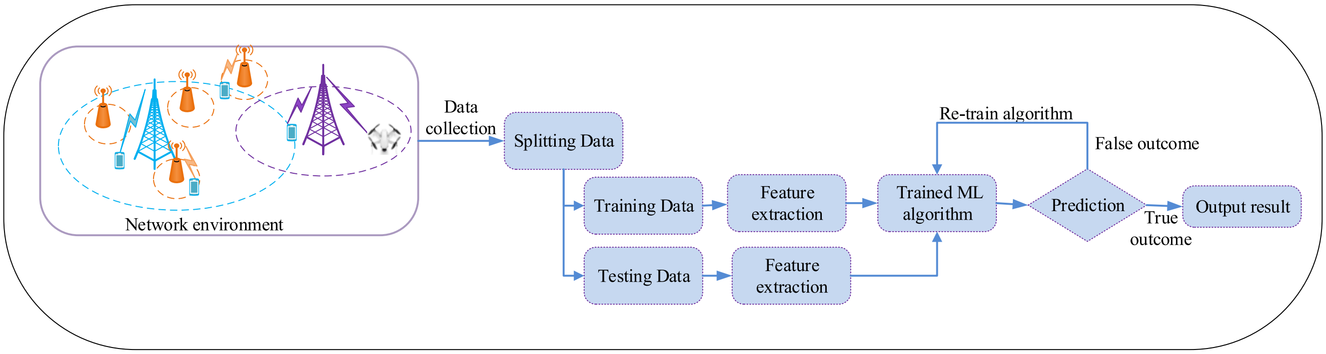

FIGURE 3. Concept of supervised ML in mobile communication systems.

scenarios (i.e., 30 km/hr and 70 km/hr). Furthermore, [39] has addressed a random waypoint mobility model over LTE network. In [40], Q-learning algorithm over a 12 small BSs deployement scenario was presented to optimize TTT, HOM, and CIO using HOF and HOPP. Mobility models include random waypoint mobility and Manhattan grid mobility model were applied in [40].

2) Q-LEARNING WITH OTHER TECHNIQUES

This section examines the various techniques combined with Q-learning.

- **FUZZY Q-LEARNING**
  FLC has been used in several research involving MRO functions, such as in [29], [30], [14], and [33]. The authors in [29] proposed the fuzzy Q-learning technique to minimize HOF, HOPP, and CDR with the use of the MRO function. However, the study was based on the LTE network. The same technique (fuzzy Q-learning) was then proposed in [30] to optimize HOM and TTT by enhancing HOR and CDR using the A3 triggering event. The LTE network was the deployment scenario in [30]. In [14], fuzzy Q-learning was offered to self-optimize the two contradictory issues of the MRO functions (i.e., RLFs and HO ping-pongs) within the LTE environment. The authors in [33] suggested a joint optimization algorithm between load balancing and MRO based on the fuzzy system and Q-learning mechanism. The KPIs (HOR, CBR, and CDR) were also applied to enhance the HCPs (HOM and traffic load). The aim of [33] is to solve the discrepancy between LBO and MRO.
- **Q-LEARNING WITH SUBTRACTIVE CLUSTERING**
  Various studies have addressed Q-learning with subtractive clustering, such as in [36] and [37]. The advantage of subjective clustering is its ability to transform the input matrices into state vectors to enhance the training process.
  The authors in [36] proposed Q-learning with subtractive clustering techniques for optimal HO settings in 5G ultra-dense networks. RSRP, SINR, and transmission distance are the performance matrices collected by the UE as historical data to improve the KPIs (HOF, HOPP, and latency). Ref. [37] proposed the subtractive clustering and Q-learning with the fuzzy logic-based algorithm. RSRP, SINR, and transmission distance were considered as input metrics to enhance system performance by investigating HOPP, HOF, throughput, and latency. The deployment scenario of [37] was based on the 5G HetNet.
- **TOPSIS DEEP REINFORCEMENT LEARNING**
  A unique study in MRO functions was presented in [42]. TOPSIS deep Q-learning algorithm is proposed to self-optimize TTT and HOM based on RSRP, SINR, and traffic load. HOF, Throughput, and HOPP were applied as a KPIs. The aim of TOPSIS technique and deep reinforcement learning mainly deep Q-learning is to preselect the target BS and auto-tunes TTT and HOM, respectively. Furthermore, the users are moving based on random waypoint mobility model over LTE ultra-dense small BSs.
- **Q-LEARNING WITH AHP-TOPSIS**
  To the best of our knowledge, [34] is the only study that addressed the MRO function using AHP-TOPSIS and Q-learning. The AHP-TOPSIS method was used for the selection of optimum target BS to enhance connection quality. Next, the Q-learning approach was used for the ideal setting of TTT and HOM. HOF and HOPP were the two KPIs used [34], as mentioned in Section IV.

VII. ISSUES AND FUTURE WORK DIRECTIONS

Several studies have been conducted regarding MRO algorithms. This section discusses the various issues followed by future work directions for each issue to facilitate further research in this field.

A. SLOW PROCESSING AND STORING ISSUES OF DATA

The Q-learning algorithm has been widely employed to solve MRO problems. However, this type of traditional reinforcement learning algorithm (Q-learning) faces the issue of maintaining and storing significantly large tables of immediate Q-values in mobile devices, thereby deteriorating system

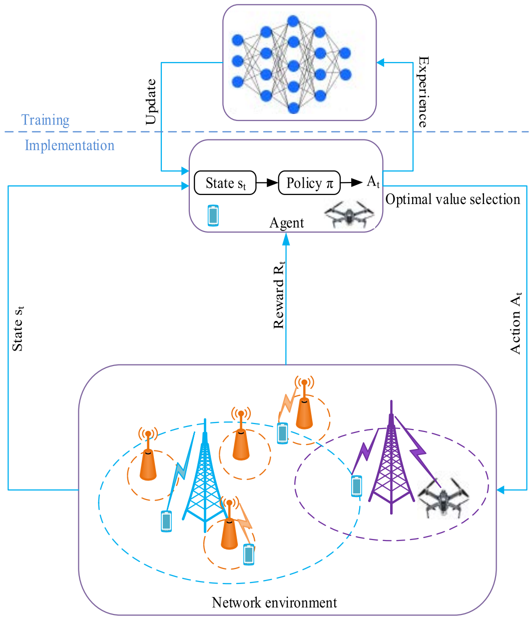

FIGURE 4. **Deep reinforcement learning in mobile networks.**

performance [92]. To overcome the limitations of reinforcement learning, deep reinforcement learning has been suggested as a potential solution in the field of wireless communication [93]. Fig. 4 presents our integration design of reinforcement learning with deep learning to achieve an optimal HO triggering setting for wireless systems. The figure shows that the optimal selection value is based on state-action- reward process. Therefore, the HO decision relays on the highest reward achieved. The HO decision using deep reinforcement learning can be obtained through the integration with the network environment without a need of a dataset which will give a significant indication for the network operators to use this technique with the dynamic network environments. However, deep reinforcement learning is a promising tool for enhancing the performance of future wireless network generations (5G and beyond). It has less memory requirements for storing the model's parameters and can mitigate slow processing and computations that face traditional reinforcement learning algorithms.

B. SUBOPTIMAL OPTIMIZATION ALGORITHMS

The HO triggering algorithms deployed in 4G cellular networks are inefficient for 5G cellular network application due to different specifications and requirements [2]. In coming years, the speed of user-connected devices will increase by up to 500 km/hr due to advancements in transportation systems. This will be a critical concern in mobility management. Further evaluations are required to achieve optimum HO for MRO functions that can meet the requirements of future wireless communication networks (5G and beyond). These evaluations must consider effective HCPs with enough KPIs to enhance system performance and accuracy. Moreover, for algorithm optimality, several optimizations should be avoided when optimizing the HCPs of the MRO function:

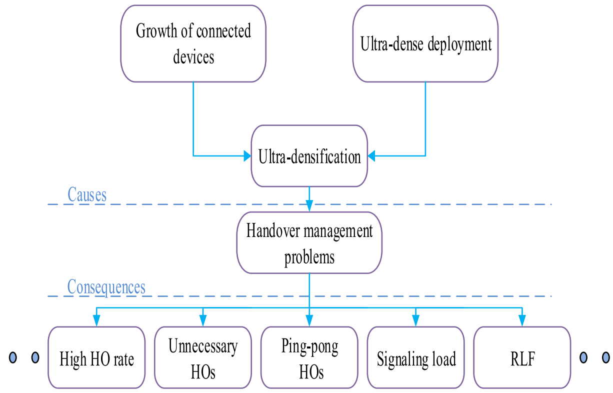

FIGURE 5. **Handover challenges in ultra-dense networks.**

- Central optimization: It has a negative impact on system performance since the HCPs setting values are applied to all users during HO regardless of the user experience. However, distributed optimization should be applied to each user individually since they face their own mobility status such as speed, RSRP, and SINR.
- Partial HO optimization: It causes quality connection issues. For instance, ignoring one of the control parameters such as TTT or HOM may lead to inaccuracy of HO optimization. Thereby, deteriorate system performance.

Therefore, up to date, no optimal HO optimization algorithm has been achieved to self-optimize the TTT and HOM precisely.

C. MASSIVE CONNECTED DEVICES WITH ULTRA-DENSE NETWORKS

In future mobile communication networks, unplanned deployments of heterogeneous ultra-dense SBSs and the number of connected devices will dramatically increase, as shown in Fig. 1. The implementation of vast amounts of SBSs per unit area using mm-waves will dramatically increase due to their short transmission range [98], [99]. This, in turn, will lead to several HO problems.

The anticipated challenges are illustrated in Fig. 5. As shown in the figure, high HO rate, unnecessary HOs, ping-pong HOs, signaling load, and RLF can dramatically increase due to ultra-densification. Addressing the consequences of HO management issues require further investigations. Models that can preserve connection quality during HOs and obtain robust mobility functions must be developed. Applying dual connectivity may contribute to minimizing RLF in dense network deployments since the UE is connected to more than one target BS.

D. INSUFFICIENT DATASET ACCESSIBILITY

Due to the protection regulation of data, obtaining sufficient and effective data to implement in the training model with the use of ML has become a challenging issue. Acquiring a dataset that includes measurement reports of the UE's mobility in HO optimization is extremely difficult. Thus, datasets are generated using several network simulators and subsequently employed for the training model. Sufficient and high-quality datasets are required as an authentication reference for different ML models. They can also be applied as a benchmark to measure the accuracy of ML models that will potentially be used in HO optimization.

E. DEVICE POWER UTILIZATION

Ultra-dense SBSs will be deployed in future mobile communication networks (5G and beyond) since these networks will implement mm-wave frequency spectrums [100], [101], [102]. Such large deployment scenarios require different systems (intra-system and inter-system), creating a complex HO process with different/similar radio access technologies [103]. The UE's measurement reports will further rise as long as the number of mm-wave frequency spectrums in ultra-dense SBSs increase. This will subsequently raise the UE's power consumption [104]. The process of locating and updating UEs within the network environment are essential processes in mobility management. The two procedures, known as tracking area update and paging, may increase the signaling overhead and power consumption in LTE and the 5G network [105]. The power consumption data can be acquired by predicting the cell location of the UE using the history information (i.e., UE's exact location, direction, and speed) [106], [107].

F. HIGH MOBILITY USERS DURING HANDOVERS

Nowadays, high speed scenarios including travelling trains and drones may reach up to 500 km/hr which will create a critical challenge for mobility management [89]. Subsequently, large number of the frequent HOs can be created due to quick occurrence of HOs which will lead to increasing in the ratio of HOPPs and RLFs. Thereby, deteriorate the quality connections. However, conditional HO is addressed as a promising solution for minimizing the ratio of unsuccessful HOs. Conditional HO defined as preparing a target BSs in advance to preserve the quality connection during HOs[102], [108], [109].

G. CONTRADICTION IN OBJECTIVES BETWEEN OPTIMIZATION PARAMETERS AND ALGORITHMS

The conflict in objectives between MRO issues (i.e., too late HO and too early HO) requires a proper setting value for the TTT and HOM. For instance, too late HO requires decreasing in TTT interval to avoid high RLF, while too early HO requires increasing in TTT interval to avoid high HOPP [8], [55]. This conflict between RLF and HOPP requires a proper configuration of the HCPs to reach to an optimal HO triggering. Furthermore, MRO function has a conflict with LBO function since they are using the same control parameter (i.e., HOM) [33], [49], [110]. Therefore, for enhancing the stability and reliability of the communication system performance, a proper HO self-optimization algorithm that is able to accurately auto-tunes HCPs during HOs is required.

TABLE 4. List of abbreviations in alphabetical order.

Item	Description
2G	2nd generation mobile network
3G	3rd generation mobile network
3GPP	Third-generation partnership project
4G	4th generation mobile network
5G	5th generation mobile network
AHP-TOPSIS	Analytic hierarchy process technique for order of preference by similarity to ideal solution
BS	Base station
CCO	Capacity optimization
CDR	Cell dropping ratio
CIO	Cell individual offset
CMAB	Contextual multi-arm bandit
DDHO	Data-driven HO optimization
ENB	Evolved node B
E-UTRAN	Evolved universal terrestrial radio access
FLC	Fuzzy logic controller
GA	Generic algorithm
GRU	Gated recurrent units
HCP	Handover control parameter
HetNet	Heterogeneous network
HO	Handover
HOF	Handover failure
HOM	Handover margin
HOP	Handover probability
HOPP	Handover ping-pong
ICIO	Inter-cell interference coordination
IT	Interruption time
KPI	Key performance indicator
LBO	Load balancing optimization
LSTM	Long short-term memory
LTE	Long-term evolution
ML	Machine learning
MRO	Mobility robustness optimization
NG-RAN	Next generation-radio access network
QoE	Quality of experience
QoS	Quality of service
RLF	Radio link failure
RSRP	Received signal reference power
RSRQ	Received signal reference quality
SBS	Small base station
SINR	Signal-to-interference-plus-noise-ratio
SON	Self-organization network
TTT	Time-to-trigger
UE	User equipment
VLC	Visible light communication

H. IGNORING QOE IN THE CELL EDGES

Majority of studies focused in reducing the mobility issues such as RLF, HOPP, and HOF without taking a consideration of QoE. However, QoE-aware in the edges of the BS brings UE's satisfaction which is a major concern for network operators. Therefore, improving the QoE in the BS's edges while enhancing the successful HO rates for the MRO is required for further studies.

However, introducing 5G-enabled technologies (i.e., edge computing, cloud radio access network, decentralization, and multiple-input multiple-output) are essential for enhancing the system performance. These 5G-enabled technologies may contribute for reducing the latency and increase the spectral efficiency.

VIII. CONCLUSION

MRO studies that employ ML techniques have been comprehensively discussed in this survey to help researchers determine the use of ML as well as which type of ML to choose.

Various state-of-the-art ML algorithms that were deployed throughout several scenarios with different parameters have been addressed in this survey. Moreover, each study addresses deployment scenario, ML type, methodology used, criteria, HCPs, KPIs, simulators, and achievements. It can be seen that differences in system performance and accuracies are present. Based on these differences, researchers can determine the most effective method that fits their research work. Furthermore, MRO functions under different network topologies are deeply addressed. Besides the MRO challenges for intra-system and inter-system mobility are discussed. In addition, this study presented a several issues for further investigations. These significant issues have been highlighted for future investigations. Furthermore, future directions of the MRO functions are addressed, such as deep reinforcement learning, conditional HO, and dual connectivity. However, achieving an optimal setting value for the HCPs of the MRO still far behind.

APPENDIX A

See Table 4.

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