Towards Positioning Error Impact Characterization and Minimization in User-Centric RAN

Waseem Raza*, Umair Sajid Hasmi†, Ali Imran* *Member IEEE*, and Sabit Ekin‡*Member IEEE*
*School of Electrical & Computer Engineering, The University of Oklahoma, USA.
†School of Electrical Engineering & Computer Science, National University of Sciences & Technology, Pakistan.
‡School of Electrical Engineering & Computer Science, Oklahoma University State University, USA.
*{waseem, ali.imran}@ou.edu †umair.hashmi@seecs.edu.pk ‡sabit.ekin@okstate.edu

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***Abstract*—The user-centric ultra-dense networks (UUDNs) confront the challenge of performance degradation because of the erroneous user equipment (UE), and data base station (DBS) positions estimated at the central controller (CC). This paper adopts the database aided approach to quantify the error impact on system-level key performance indicators (KPIs) under various configuration and optimization parameters (COPs). Although the performance fall is consistent with the increase in error radius of both UEs and DBS positions, its impact can be alleviated by extrapolating on the erroneous database and adopting to new COP values. To realize this, time-series (TS) forecasting is utilized to determine the extent of compensation and COP variations. Results compared for two TS based schemes show that a significant portion, more than 50%, of the decreased performance can be recovered by the suggested adoption in the COP values.**

***Index Terms*—UUDNs, DBS, Central Controller, Time-Series Forecasting, COPs, KPIs.**

I. Introduction

Wireless and mobile networks are service-oriented businesses at the massive scale focused on providing better connectivity experience to the millions of end users. The designed network should be user-centric, not only in the marketing connotation, but also in the literal architectural design paradigm [1]. Despite the drastic increase in the link quality and network capacity due to the reduced average distances in UDNs, the rise in interference becomes a crucially limiting factor especially in the scenarios of larger BS density [2]. The idea of the UDNs was evolved to user-centric UDNs (UUDNs) by revising the role of traditional BS-centric cells and their relevance in the CRAN architecture [3]. UUDNs consider a single or a group of UEs at the center of cell and a remote radio head within the cell is activated to serve the respective UE(s). This offers the significant capacity benefits by eliminating the cell-edge users and allowing the dynamic cooperative transmission and reception; handled locally, and reduce the signaling and computational overheads compared to those in network wide cooperation [3]. While there have been multiple variants of UUDNs that have demonstrated higher user quality of experience and spectral, energy efficiencies [4], [5]; they all rely on assumption on accurate knowledge of user and base station locations.

With the increasing complexity of the network, and surge of the artificial intelligence (Al) and machine learning (ML) based solutions, the data driven modeling is being envisioned not as a preference but an inevitable characteristic of the future mobile networks [6], [7]. It might not replace the traditional analytical/mathematical models-based techniques but will certainly complement on different levels of the network design to improve the network performance in future generations. Data driven modeling is being utilized in different contexts, such as: to predict the network faults and proactive counteraction, to model the user mobility for efficient handovers, and to utilize it for learning the load variations and balancing solutions [8]. Although most of the existing work is carried out in BS-centric network, some works utilize the AI and ML techniques in the user-centric network settings when data driven approach is indirectly followed. In [9], authors utilize the K-way normalized cut clustering algorithm to find the optimum sparse code multiple access code-book allocation which can minimize the network interference and maximize the system throughput subject to the QoS constraints. Similarly, in [10] the multi-branch deep residual learning for user clustering and cooperative beamforming is used in user-centric networks. Finally, ML is utilized to approximate the distribution of the aggregated interference power for the application of spatial spectrum sensing in the user-centric networks [11].

There have been several studies in literature focusing on the characterization the positioning error and quantization loss [12], [13], [14]. The authors in [12] model the effects of error in UEs positions on the cell edge reliability and cell coverage probability for the cases of shadowing and non-shadowing environments. This work is extended in [13] to, include the error of BS positions in the analysis and utilize the minimization of drive test (MDT) data based autonomous coverage estimation technique. Authors report the sub-optimal performance of the coverage estimation in the presence of error in geographical information. The work in [14] employs the fluid model to characterize the signal to interference ratio (SIR) in database aided user association with control and data plane split architecture. Similar to [13] this study is carried out for the case of path loss only, and path loss-and-shadowing channels. The inaccuracies in positioning techniques lead to the flawed association resulting in degraded SIR and area spectral efficiency (ASE), which becomes severe when the BS density is increased, a common situation in UDNs. Another work considering the geographical inaccuracies on the coverage estimation is carried out in [15]. In this work error in user positions due to GPS measurement uncertainties and quantization loss due to the division of the coverage area in the bins are considered. Authors investigate the interplay between the positioning error and quantization loss in coverage estimation and show that there exists an optimal bin-width; a function of positioning error and user density, which gives the maximum coverage. Although these works are good initial attempts to quantify the error impact, they are specific for the BS networks only.

While the accurate estimation of the UE's and BS positions has been significant in the legacy BS-centric network to efficiently perform the network automation and self-healing tasks, it's importance in the UUDNs cannot be overstated. The working of these networks requires the accurate location information of the UEs and DBS at the central controller (CC) to form the non-overlapping virtual cells termed as service zones (Szones) and activate the corresponding DBS. It is generally assumed that the CC is an omniscient entity having the error free locations of all UEs and DBS. However, every location estimation approach, such as GPS, has an inherent inaccuracy associated with it. Hence, the errors in locations of the UEs and DBS cannot be ignored because they can lead to the formation of overlapping Szones, and inappropriate DBS activation, causing the eventual decrease in KPI values. Hence, the very essence of UUDNs formed by the non-overlapping and interfering Szones is undermined by the presence of significant errors in the user and DBS positions. Further the optimization solution to maximize these KPIs under various COPs are also affected by the abovementioned errors, leading to the sub-optimal solutions. Hence, this work is focused on studying the impact of errors in UEs and DBS positions on various system-level KPIs in UUDNs by adapting the network level simulations and data driven approach. *To the best of authors knowledge this is the first work to carry out the error modeling in the UUDNs following the network level simulations and data driven solutions.* The contribution of the proposed work is summarized in the following points.

- The first contribution is to simulate the UUDNs module in 3GPP compliant 5G system-level simulator published in [12]. The UUDNs is capable for generating the databases of important KPIs related to different COPs under the assumption of ideal and erroneous positioning.
- The error in UEs and DBS positions, jointly termed as the underlying error radius (UER), is considered; to generate the UER-KPI database and characterize the performance degradation with respect to error radii.
- Then UUDNs are simulated to generate the COP-KPI data for both the ideal and non-ideal cases. The performance falls previously observed is also validated in the COP-KPI data generation.
- Finally, TS forecasting is utilized on the non-ideal database to find the adjustments in the COP values for mitigating the performance fall. The mitigation solution by two different TS approaches is analyzed and compared with the ideal counterpart to determine the accuracy of the solution and extent to which the compensation is possible.

The rest of paper is organized as follows. In Section II, system model, motivation for the proposed error modeling work and details of the framework are discussed. Section III gives the detailed implementation of the synthetic data generation mechanism for the UER-KPI and COP-KPI databases, discussing the usage of these databases for error impact characterization and minimization. The TS mechanism to counter the error impact in the COP-KPI data is also explained in the Section III-C. In Section IV, we discuss the simulation setup and compare the results for the error impact characterization and TS based solution to reduce the impact. Finally, the conclusion and future work are given in Section IV.

II. System Model, Motivation and Proposed Framework

Following the UC-RAN proposed in [13] we consider two independent stationary Poisson point processes (SPPP) for the distribution of UEs and DBS in the network area and utilize the Matern hard core type II (MHC-II) thinning process to model the scheduled users. The SPPP requires underlying densities of UEs and DBS; λ_{ues}, λ_{dbs}; to randomly distribute the UEs and DBSs in the given geographical area. The average number of the UEs (DBS) in the network is characterized by the $\lambda_{ues}A$, where A is the area, The average number of DBS in a Szone can also be characterized by its respective density and Lebesgue measure of the circular disc with radius R_{sz}, i.e., $\lambda_{ues} = \pi\, R_{sz}^2$. The MHC-II thinning process takes the initial user distribution and radius of Szone as input and results in the set of scheduled users, each being on the center of the non-overlapping Szone, in each TTI. The channel is modeled using the two-slope path loss model with log-normal shadowing, and one DBS from each Szone with highest RSRP is activated. For this work, we assume that all DBS are equipped with a single omni-directional antenna and transmit with same power which can can be controlled from the CC. The system is assumed to be interference limited only as the thermal noise is negligible for this work. The positioning error analysis is manifested by the difference in the actual and estimated positions of UEs and DBS, where actual positions are uniformly located around their estimated (reported) positions within a circular disc of error radius. For every setting of the scheduled UEs and activated DBS in each TTI, we compute the underlying KPIs and maintain their values in a database.

A. Motivation for the Error Modeling

As explained in the previous section, two important steps of the user-centric networks working are the scheduling, and DBS activation. By scheduling, here we mean the formation of the non-overlapping Szone carried out by the thinning process of MHC-II, where each user is tagged with a marker, a uniform random value between 0 and 1, which inversely corresponds to its scheduling priority. The user who has the highest scheduling priority in a neighborhood radius R_{sz} is scheduled for receiving data from the activated DBS. The activation of the best available DBS in the Szone is coupled with the user scheduling as the selected DBS to serve a scheduled UE should be within the R_{sz} distance from that UE. Both processes are carried out by the CC located on the macro base station or BBU pool. The location information of the UEs and DBSs has a vital role to play in both processes. However,

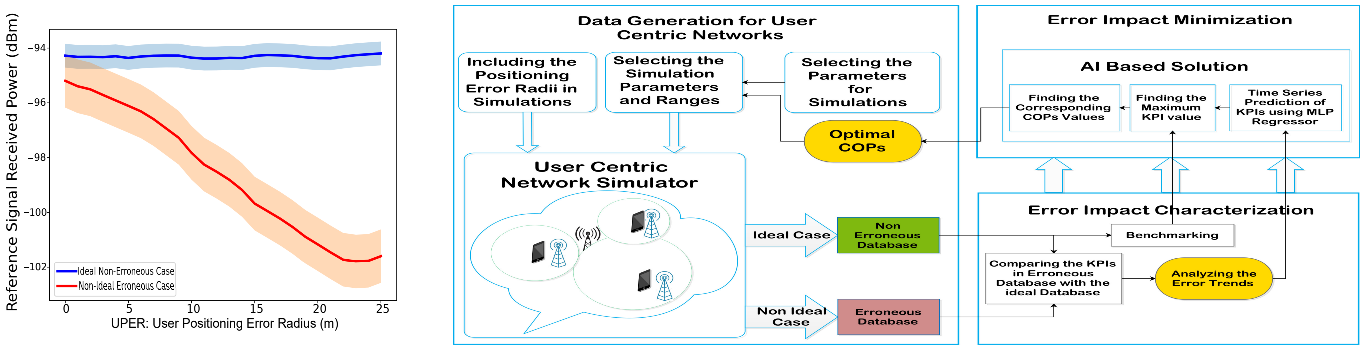


Figure 1: (a). The increasing fall in RSRP with respect to user positioning error radius (UPER), (b). The framework for error impact characterization and its minimization using the TS based modeling in UC-RAN.

the CC is not an all-knowing entity and has to rely on some global (or local) positioning techniques [17], to estimate the location information of the UEs and DBSs. Although the required location accuracy is dependent on various factors such as the environment (indoor, outdoor, urban or rural), applications etc, every estimation technique has inherent error associated to it. Hence, the location estimation error in the UEs and DBSs positions cannot be ruled out especially in the large geographical area. To further emphasize the proposed work, we plot the impact of error in user positioning, termed as UPER, on average RSRP at the schedule UEs as shown in Fig. 1a, details of the implementation parameters given in Table I. The RSRP values are averaged over all UEs and then over all transmission time intervals (TTIs), while the shaded region shows the range of deviation of these values. The error radius on the x-axis corresponds to the maximum possible deviation the UEs can have, where for a certain error radius, the UEs deviation from the original position is uniformly distributed but confined within the circular of error radius. For this result, we assume that the DBS positions are not deviated. As it can be observed that in the ideal (non-erroneous) case the RSRP values remains largely unchanged because it is assumed that CC is omniscient to the exact location information. However, as the error in UEs positions increases there is a noticeable decrease in the RSRP. It should be noted that in non-ideal case the CC takes erroneous values of UEs positions for the Szone formation, UEs-DBS association and activation, and resource allocation. However, for the calculation of RSRP in non ideal case, ideal UEs positions are considered to observe the impact of errors on them. Hence, the erroneous position based Szone formation can generally lead to relatively farther DBS activation, which not only gives the lower RSRP but also increases the interference for the neighboring Szone leading to reduction in overall average SIR and negatively effecting the other relevant KPIs. Fig. 1a only shows the impact of error in UEs positions on the single KPIs, and there occurs significant decrease in the RSRP values, this situation would become worse in the simultaneous presence of both the UEs and DBS positioning errors. Hence, there is a need for a thorough study of these errors and their impact on the KPIs. Further, to ensure that this error impact is not skewed by a particular COP setting, we proposed to extend this error impact characterization for various COP-KPI combinations.

B. Proposed Framework: Database-aided Error Modeling

The proposed database aided approach to model the impact of errors on system-level KPIs in UC-RAN networks is discussed in this section. The framework is divided in three different stages, as shown in Fig. 1b. The data generation phase includes the UUDNs simulator which takes in different values of the underlying COPs, along with the other simulating parameters, such as the bin size, network area, simulation time measured in TTIs etc. It also has the flexibility to include or exclude the value of the error radii, for both the UEs and DBS positioning errors. It generates the TTI based traces of various under study KPIs such as the *average RSRP, Coverage Probability, average SIR, ASE and Network Energy Efficiency (NEE)*. For all these KPIs the database for ideal case is used for benchmarking by comparing it with non-ideal cases in the second block. Finally, the third block focuses to counter the impact of errors on the KPIs performance by employing the TS forecasting and suggesting the variations in COPs.

III. Synthetic Data Generation Mechanism

In this section, we detail out the mechanism followed to generate the databases for different COP-KPI settings under the assumption of erroneous and non-erroneous conditions. These databases can be utilized by the CC to schedule the sZone UEs and manage the activation of DBS. Further, the implementation of data driven solution for modeling and optimization of the network at the CC also requires the data collection and database formation. To realize these in UUDNs, the synthetic data generation approach using the SyntheticNET [16]: a 3GPP compliant system-level simulator to enable the AI based techniques for 5G and beyond networks, is followed. The user-centricity is added into the SyntheticNET as a module where instead of conventional BS-centric cell formation, the non-overlapping UE-centric Szones are formed using MHC-II process. The initial deployment of UEs and DBS is carried out by the Poisson distribution base stochastic modeling for the given densities. Then in each TTI, MHC-II process is utilized to determine the set of scheduled users and form an Szone of given radius R_{sz} around each schedule user. The DBS activation is based on the highest RSRP and only those scheduled UEs are served which have at least one DBS in the Szone. To note the effect of the UPER and DPER, their actual (estimated) positions are used in all steps of network formation: Szone formation, DBS activation and KPI calculations for ideal (erroneous) databases.

In terms of the execution, the simulator is composed of two components, one termed as the front end (FE) and the other as back end (BE). The parameter setting which involves deciding the values and ranges of the underlying constant and varying parameters for the respective database generation are carried out in the FE. The BE is called, in serial or parallel depending on the available computing resources, for each parameter combination, where it performs the network deployment according to the set parameters, runs the simulations over the set TTI horizon and returns the intended KPIs results.

A. UER-KPI and COP-KPI Databases

As mentioned earlier, the simulator is flexible to generate two different kinds of databases, named as the UER-KPI and COP-KPI. The UER-KPI database is used for the error impact characterization as the effect of UPER and DPER on the KPIs is measured and stored for both the ideal and non-ideal cases. Specifically, in the UER-KPI database, the combinations of UPER and DPER are executed and KPI values are measured over the TTI horizon, while the COPs and non-optimization parameters (NOPs) are treated same as all have fixed values. The results of this error impact characterization is shown in Fig. 3, where the error in respective KPIs are depicted with respect to UPER and DPER. In the COP-KPI database UPER and DPER are fixed along with other NOPs, but the COP values are varied to observe their impact on KPIs. The COPs which can be modeled in our simulator include the UEs density, DBS density, Szone radius, transmit power, RSRP threshold (used for coverage probability) and SIR threshold (used for spectral efficiency). The simulator can generate the various KPIs, such as the RSRP, Success Probability, SIR which are averaged over all UEs (hence termed as UE level KPIs) and stored for each TTI, whereas the network level KPIs include the coverage probability, ASE, and NEE, averaged over the TTIs only. For the COP-KPI database in this work, we resort to three COPs i.e., DBS density, Szone radius and transmit power and generate the ideal and non-ideal databases, with UPER and DPER of 15, for three KPIs, i.e., RSRP; from the UE level KPIs and ASE and NEE from the system-level KPIs for the proposed error analysis. More details of the parameter values for generating the UER-KPI and COP-KPI databases are given in the Table I.

B. Countering the Error Impact in COP-KPI Database

In this section, we focus on the approach of adopting the counter measures to dilute the error impact and recover some percentage of the performance loss. One approach to resolve the positioning error problem is to utilize the better location estimation techniques, which might require expensive equipment and so on. However, this work is focused to analyze the network capability to counteract the KPI's fall by adjusting it COPs values. To further explain this process and challenges associated with this, we first discuss the RSRP databases generated for the ideal and non-ideal case as depicted in Fig. 2. In this result, three important COPs, having 10 values for each and given in the order of c_o=*[Transmit Power, Szone Radius, and DBS Density]* vary from the $[15,\ 10,\ 0.0005]$ to $[30$ dBm, 50 m, 0.00125 km$^{-2}]$, generating the overall databases size of $10^3 = 1000$ instances. With UPER and DPER of 15 m, a significant fall in the RSRP can be noted which can adversely affect not only on the system performance but also on the data driven optimization solutions aimed to maximize the network performance for this KPI. Hence, there is significant need for the countermeasures to mitigate the effect of the positioning errors. The careful observation of the COP-KPI data suggests that along with the seasonal rise and fall, there occurs a trend of linear rise in the KPI values with respect to COPs in both the ideal and non-ideal cases. This suggests that a further increase in COP values for non-ideal case can bring its values closer to the ideal situation. However, unlike most of the ML based solutions which are focused on the interpolation, this trend requires to extrapolate, predict out-of-bound values, on the COP-KPI relations. To undertake this challenge, one of the basic extrapolating ML technique, TS forecasting is utilized to learn the KPIs trend and predict the next possible maximum values. There are various TS regressor solutions available, however, we resort to the seasonal auto regressive integrated moving average (SARIMA) and multi-layer perceptron (MLP) models, as SARIMA model is suitable for the TS forecasting where the available data involves the seasonal patterns.

The key challenge in this approach is that unlike the conventional 1-D independent variable where increase and decrease can be directly visualized on an axis, the COP combination is a three-dimensional pattern in which only one parameter is changed between two successive instances. Hence, the increase in COPs combination is not straightforward to observe in the database. Therefore the corresponding COP values cannot be directly extracted from the forecasted KPIs unless we already have a database for those COP values, which can be used for this purpose and performance evaluation of the TS based solutions. To tackle this challenge, we assume the already generated *10 values per COP based* databases (referred as DB-10) as baselines and indexed out two databases from it named as DB-08, and DB-09. The DB-08 is taken by assuming that each COP has the first 8 of the original 10 values, hence the COPs corresponding to only those values in DB-10 are extracted for this case. The TS regressor solutions are trained on all $8^3 = 512$ values of DB-08 to learn the KPIs trend and forecast the $9^3 - 8^3 = 217$ extra values of the second database (DB-09), whose generation is similar to DB-09. The DB-09 KPI values can be utilized to validate the forecasted results and measure the forecasting accuracy and percentage recovery. Specifically, the maximum forecasted values are compared to the pre-generated values of DB-09 database, and the closest possible KPI value from DB-09 is taken as solution and its COP combination is given as the suggested solution.

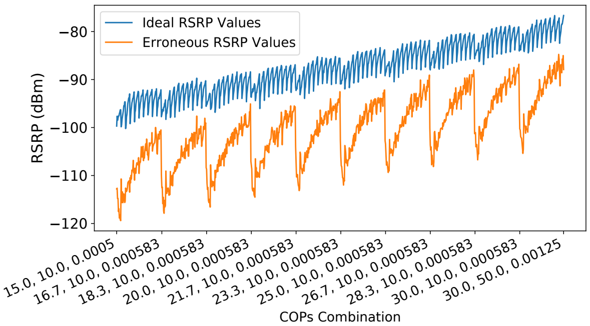


Figure 2: The COP-KPI database trends with the ideal and non ideal cases.

Illustration: An example for the case of RSRP is detailed out here, for other KPIs similar approach is followed. The maximum RSRP in DB-08 for the ideal case is -80.53 dBm for the COPs combination of $c_i = [26.66, 36.66, 0.001081]$ which falls to -91.27 dBm due to UPER and DPER of 15 m. Now, taking the maximum RSRP of non ideal case in DB-09, i.e., $v_t = -87.45$ dB, corresponding to $c_t = [28.33, 45.55, 0.001164]$ as the achievable improvement, the abovementioned TS models are trained on the DB-08 and predict the values of forecast horizon. For the RSRP case, the maximum values predicted by the SARIMA and MLP Regressor (MLP-REG) are -87.82 and -87.52 dBm, respectively. The minute difference from the predetermined target, v_t is used as the forecasting error and c_t has the suggested new values of the COPs to somewhat mitigate the effect of positioning errors. Hence, by changing the COPs to this c_t combination, the RSRP can be improved.

Table I: Simulation parameters for generating the UER-KPI and COP-KPI databases. EMP: Error modeling parameters

Parameter Name	Parameter Type	UER-KPI Scenario	COP-KPI Scenario
User Density	NOP	0.0005	0.0005
DBS Density	COP	0.0005	0.0005-0.0125
Transmit Power	COP	20 dBm	15-30 dBm
Szone Radius	COP	25 m	10-50 m
UPER	EMP	0 – 25 m	15 m
DPER	EMP	0 – 25 m	15 m
Shadowing	NOP	4	4
Network Area	NOP	1km sq	1km sq
Bin Size	NOP	10	10
Simulation Time	NOP	100	100

IV. Simulation Results

This section discussed the results of proposed data-base aided error impact characterization and the solutions. While the detailed implementation of simulator for generating the databases is briefly discussed in Section III, the specifics of 3GPP compliant 5G system-level simulations carried out to model the network parameters in a geographical area of interest are given in Table I. For the UER-KPI database, simulator takes various combination of the error radius and generates the corresponding values of the KPIs. Each KPI has the ideal and erroneous variant, which are compared to characterize the error in terms of performance fall.

Table II: The parameters of SARIMA and MLP-REG models used for the TS forecasting for different KPIs under study.

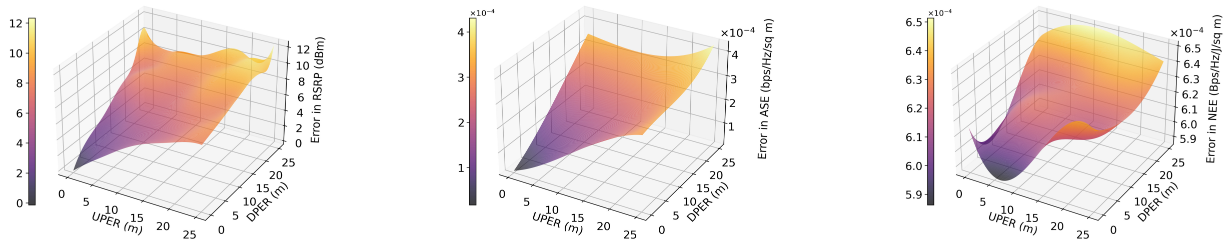
	SARIMA Model Parameters		MLP-REG Parameters	
	Trend Elements (p, d, q)	Seasonal Elements (P, D, Q, m)	Model Specs (l, n)	Solver and Activation Functions
RSRP	(1, 1, 1)	(1, 1, 1, 64)	(5, 20)	(lbfgs, relu)
ASE	(1, 1, 1)	(1, 0, 1, 64)	(10, 50)	(adam, relu)
NEE	(1, 1, 1)	(1, 0, 0, 64)	(10, 50)	(lbfgs, tanh)

A. Error Characterization Results

The results of the error impact characterization on KPIs understudy are discussed here. The fall in RSRP, ASE and NEE with respect to the UPER and DPER is shown in Fig. 3. For this analysis we assume the fixed Szone radius of 50 m, transmit power of 20 dBm and UEs and DBS densities of 0.0005 Km^{-2}. The UPER and DPER vary from a minimum value of 0, referring to the ideal condition, to the maximum value of 25 m (half of the sZone radius). Figure contains the error in the RSRP, ASE and NEE values, which is computed by differing from the ideal values, with respect to UPER and DPER. The general trend in all these results suggests that as UPER and DPER increase, the fall in each KPI performance increases. However, the specific fluctuations are idiosyncratic to the respective KPI inherent nature and to the fact that these trends are averaged over all UEs and TTIs. An important observation to note is that the effect of error in one parameter is more pronounced while the error in the other one is lower. Specifically, the RSRP results show that both the UPER and DPER affect adversely on RSRP. However, the impact of UPER on the error in RSRP is significant when the DBS error is low, this is because the uncertainty in DBS position in this situation can lead to some cases when even the erroneous DBSs are located closer to the UEs which contributes towards the RSRP improvement.

B. Time Series Forecasting Based Error Alleviation Results

As discussed in Section III-B, for all the KPIs, we employ MLP-REG and SARIMA models for the TS forecasting with relevant parameters, selected after extensive search are listed in Table II and results for models' errors and performance is shown in Fig.4. The percentage of each KPI performance fall and recovery by the comparing models are depicted in 4a. Although the fall in RSRP was visualized in Fig. 2, the left three bars show the fall in all KPIs, average over TTIs. To show the impact of compensation, the KPIs percentage fall after recovery by the respective TS schemes is plotted. These results depict that, in the given network settings although a significant of the KPI fall can be recovered by adopting the COP values, the non erroneous case cannot be achieved because of sufficiently high error radius. Comparing the SARIMA and



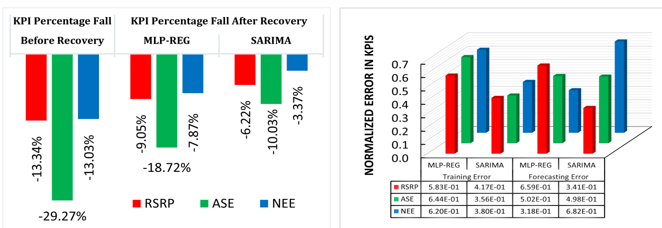
(a) The trend of the error in RSRP with respect to UPER and DPER.

(b) The trend of the error in ASE with respect to UPER and DPER.

(c) The trend of the error in NEE with respect to UPER and DPER

Figure 3: The impact of the error in the User and DBS positioning error radii (UPER and DPER) on various KPIs.

MLP-REG progress, it is evident that former models are able to outperform the later one for all KPIs because of its natural tendency to learn the seasonal patterns in the database. It is corroborated by the training and forecasting errors of all KPIs where SARIMA model achieves better performance in all comparisons except the NEE forecasting. The training and forecasting errors are independently normalized between two comparing schemes to better visualize their performance.



(a) Percentage decrease and retrieval of underlying KPIs

(b) Training and forecasting errors for comparing models.

Figure 4: Comparing the MLP-REG and SARIMA Models.

V. Conclusion

The error in UEs and DBS positions cause significant problems in the Szone creation, DBS activation and resource allocation stages of the UUDNs. To quantify the impact of these errors in UUDNs, this paper employs to the synthetic database aided approach to show continuous fall in KPIs as the UPER and DPER increase. To dilute the error impact, this work applies the TS forecasting on the erroneous database and determine the enhanced COPs' combinations to make up for the decreased KPIs. The comparative analysis of MLP-REG with the SARIMA model shows that the later has higher prediction accuracy and compensation efficiency. In future, we aim to extend this work by observing the analysis for more COP-KPI databases, and analyze the potential of TS based error impact alleviation on different training and prediction window sizes, which might further improve the compensation progress.

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