Cell Outage Detection in Heterogeneous Networks with Separated Control and Data Plane

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***Abstract*—In this paper, we propose a data cell outage detection scheme for heterogeneous networks (HetNets) with separated control and data plane. We consider a HetNet where the Control Network Layer (CNL) provides ubiquitous network access while Data Network Layer (DNL) provides high data rate transmission to low mobility User Terminals (UTs). Furthermore, network functionalities such as paging and system information broadcast are provided by the CNL to all active UTs, hence, the CNL is aware of all active UTs association. Based on this observation, we categorize our data cell outage detection scheme into the trigger phase and detection phase. In the former, the CNL monitors all UT-data base station association and triggers detection when irregularities occurs in the association, while the later utilizes a grey prediction model on the UTs' reference signal received power (RSRP) statistics to determine the existence of an outage. The simulation results indicate that the proposed scheme can detect the data cell outage problem in a reliable manner.**

I. Introduction

Recently, extensive research work has focused on the concept of self-organizing networks (SON), which involves the autonomic operation of the network by using self-configuration, self-optimization and self-healing functionalities [1], [2]. In this paper, we focus on cell outage detection which is a sub-division of cell outage management in SON's self-healing functionality [3], [4]. Cell outage detection aim to autonomously detect outage cells, i.e., cells that are not operating properly due to possible failure, which may include external failure such as power supply or network connectivity, or even misconfiguration [5]–[8]. In some cases, cell outage can easily be detected by the operations and support system (OSS), while some detection might require unplanned site visits, which is a costly task. In addition, it may take hours or days for the cell outage to be detected, thus resulting in pronounced reduction in capacity and quality of service, and coverage gap [6], [7]. Hence, automatic detection of cell outage is a necessity, and, it has been included in recent specification for LTE [5].

Cell outage detection algorithms proposed in [6]–[9] have focused on macrocells. It is expected that future cellular networks will be heterogeneous networks (HetNets), i.e., a mix of macrocells for ubiquitous user experience and small cells for high data rate transmission. Hence, the algorithms proposed in [7]–[9] are not suitable for such networks due to the dense deployment nature of the small cells in the HetNets as compared to the macro only deployments. Furthermore, there is high tendency of having a sparse user statistics in small cells, since they usually support very few user terminals (UTs) as compared to macrocells. Recently, [6] proposed a cooperative femtocell outage detection scheme which is based on a distributed outage trigger mechanism and sequential hypothesis testing.

A new paradigm of HetNets architecture that allows for a more energy efficient operation with reduced overhead via decoupling the data and control/signalling plane at the air interphase has recently been proposed in [10]–[12]. In such layered architecture, the control network layer (CNL), which is made up of macrocells provide ubiquitous network access. On the other hand, the data network layer (DNL), which is composed of small cells, support high data rate transmission. Hence, UTs requiring high data rate transmission are connected to both the CNL and DNL while low rate UTs are connected to just the CNL. According to the state classification in [11] and [12], the CNL is always aware of every UT-small cell association in its coverage. In such architecture, the CNL can passively monitor the reference signal received power (RSRP) statistics of every UT-small cell association in its coverage while also maintaining a regular update of the RSRP statistics between the macrocell and each UT. This gives a new perspective to the cell outage detection contrary to [6], where such functionality layer separation is not considered.

In this paper, we present data cell outage detection scheme for HetNets with separated control and data plane. In other to reduce the detection overhead caused by unnecessary detection, we categorise the data cell outage detection into outage trigger and detection phases. The outage trigger phase monitor the UT-small cell association, handover performance and radio link failure indication, and triggers outage detection when it discovers irregularities in UT-small cell association. The outage detection phase leverages on the grey prediction model [13]–[17] to tackle the detection problem. The rest of the paper is organized as follows. In Section II, we present the system architecture which includes description of the layered HetNets structure, system model and observations leading to the detection scheme. In Section III, we present the data cell outage detection scheme, detailing the outage trigger and detection phase. In the later, we utilize grey prediction approach to formulate the detection problem. In Section IV, we present simulation results and discussions. Finally, Section V concludes the paper.

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II. System Architecture

A. Layered Structure

We consider the separation of the HetNets architecture into the layered structure as presented in [11], where the CNL provides ubiquitous network access to UTs while the DNL support high data rate transmission to UTs. As in [11] and [12], the CNL is composed of macro BSs which we refer to as control BSs while the DNL is made up of discontinuous small BSs which we call data BSs[1]. As a result of this separation, network functionality such as paging, multicast, synchronization and system information broadcast which are required by UTs in the detached or idle states are provided by the CNL. Furthermore, the CNL is also responsible for data transmission for low data rate and high mobility UTs as well as higher layer control information transmission such as cell handover, radio resource control (RRC) connection management and other functions. As mentioned earlier, the main function of the DNL is to support high data rate transmission for the active UTs hence, the functionality of this layer are unicast and synchronization. Based on this layered structure, an active UT can be served by either both the CNL and DNL at the same time for high data rate and low mobility transmission which is referred to as d-active state, or just the CNL for low rate or high mobility transmission denoted by c-active state. Consequently, the transmission from the frame on the DNL can be switched off when there is no high data rate transmission from the active UTs.

B. System Model

We consider M data BSs and one control BS providing DNL and CNL functionalities, respectively, as illustrated in Fig. 1. Focusing on detecting outage in the data BSs, we consider an ideal CNL scenario where the control BS cannot experience outage. Hence, outage can only be experienced by the data BSs. We consider that m active high data rate UTs are been served by both the data and control BS while c active low rate UTs are been served by only the control BS. The m high data rate UTs transmit and receive data from their associated data BS and periodically reports their UT-data BS RSRP statistic to the control BS. Furthermore, they also sends periodic context information update to the CNL, which includes, their location information, capability information, and other information essential for the network to identify them [11]. Hence, the UTs also periodically report its measured RSRP from the control BS back to the CNL. The reported RSRP between u^{th} UT and node F is modeled as

$$r_{uF} = Pt_{FB}(\text{dBm}) - PL_{u,FB}(\text{dB}) + X_{u,FB}, \qquad (1)$$

where Pt_{FB} is the node F's transmit power, $PL_{u,FB}$ denotes the pathloss between the u^{th} UT and F [18], and $X_{u,FB}$ is a zero-mean Gaussian distributed random variable (in dB) with standard deviation σ (also in dB).

[1]In this paper, data cell also refer to small cell or data BS while control cell also refer to macrocell or control BS.

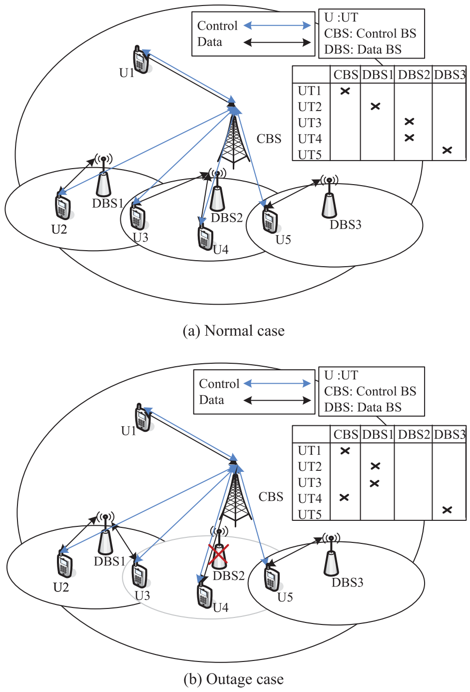

Fig. 1. *Cases in data cell outage detection*

We assume that the CNL knows the location of all the small cells and that the location of the UTs is unknown to either the CNL or DNL. In case of an handover without a change in control BS, a UT in the d-active state first transit to the c-active state then transit back to the d-active state after handover for continuous data transmission, as recommended in [11].

C. Observation

In order to design a data cell outage detection architecture, we first illustrate the UT association in the normal and outage cases in Fig. 1. In the normal case all data BSs operate normally and the high rate UTs (U2 – U5) are associated with both the control BS and data BS while the low rate UT (U1) is associated with just the control BS, as illustrated in Fig. 1a. In case of an outage on DBS2, U3 and U4 remain connected with the control BS for control signalling as illustrated in Fig. 1b; however, they both experience a loss in data link at the point of outage. After performing data cell search, U3 becomes associated with DBS1 for data transmission, since DBS1 can meet its data rate demand. On the other hand, in the case of U4, it becomes associated with the CBS for data transmission since it is not in the coverage of any non-outage DBS. The control BS can keep track of every UT-data BS association in its coverage and trigger an outage detection process if it discovers some irregularities in the association. In this case, the CBS triggers outage detection process since a change in UT association has occurred without any prior handover notification. Note that the control BS is always aware of any change in the state of the UT, i.e., changes from active to idle state, idle to detached state and vice versa.

III. Data Cell Outage Detection

The data cell outage detection process is categorised into the trigger and detection phases, as illustrated in Fig. 2. The control BS receives a periodic update of the RSRP of each UT to its associated data BS and stores this value in a database. In the trigger stage, the control BS monitors the UT-data BS association and triggers the detection stage if there are irregularities in UT association.

Given that the outage of data BS, d, is to be detected. In the detection stage, the control BS predicts the RSRP of all L UTs associated with the data BS d by using RSRP data from the database. For each of the UTs, the control BS compares the predicted RSRP value, v_u, with the RSRP value reported from its present association, r_u, to determine the likelihood of an outage. Based on the predicted RSRP values, the control BS then compares the ratio of the number of UTs that are supposed to be associated with the data base d to L with a predefined threshold, μ. If the ratio is higher than the threshold, the control BS makes a decision that data BS, d, experiences outage. Otherwise the control BS decides that the data BS d is normal.

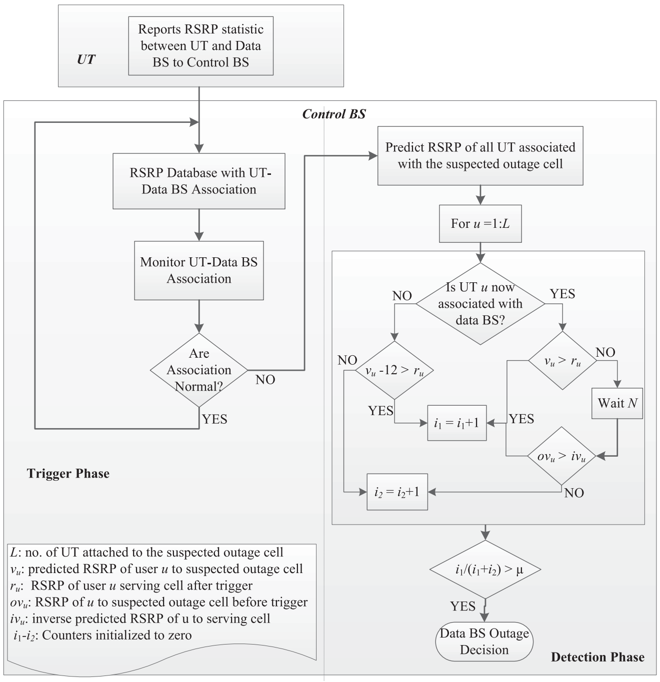

Fig. 2. *Data cell outage detection architecture overview*

A. Outage Trigger Phase

The outage trigger stage involves the control BS monitoring the UT-data BS association and triggering outage detection when irregularities in the association occurs. The control BS is aware of any change in UT-data BS association as a result of handover or radio link failure. As mentioned earlier, the control BS is also aware of any state change in the UT such as a change from active to idle state, idle to detached state and vice versa. Furthermore, the conditions for data BS to enter the idle or sleep mode is known to CNL. For example, the data BS could be allowed to enter sleep mode if the number of active UTs is lower than a certain predefined threshold during the last scheduling time interval. Irregularities in UT-data BS association occurs when all UTs attached to a particular data BS becomes associated with another data BS or the control BS (for data transmission) without prior handover initiation process or the occurrence of a change in state of all the UTs or radio link failure notification from all the UTs or the data BS going into sleeping mode.

B. Outage Detection Phase

Once the outage detection phase is triggered, the control BS can detect outage of the data BS by predicting the RSRP of all the UT that were associated with it prior to the outage. We utilize the grey prediction model (GM), which has been extensively used in handover, positioning and general forecasting algorithms [13]–[17], for our prediction model.

1) Grey Prediction Approach: In grey system theory, $GM(\bar{n}, \bar{m})$ denotes a grey model, where $\bar{n}$ is the order of the differential equation and $\bar{m}$ is the number of variable. Here we focus on $GM(1,1)$ which is a time series forecasting model and also widely used. According to [13], the $GM(1,1)$ model can only be used on positive data sequence. Note that the RSRP values are always positive, hence, the grey model can be used to predict the next RSRP value from data points obtained in the database.

The three basic operations in grey prediction are the accumulated generating operation (AGO); the inverse accumulated generating operation (IAGO) and grey modelling. By using AGO, an irregular raw data can be transformed into a regular data which can be used to construct a model in grey differential equation. The non-negative RSRP data sequence of user u prior to the outage is denoted as

$$r_u^{(0)} = \left(r_u^{(0)}(1)\,, r_u^{(0)}(2)\,, r_u^{(0)}(3)\,, \ldots, r_u^{(0)}(n) \right), \quad \forall n \geq 4. \tag{2}$$

When the sequence given (2) is subjected to AGO, the following sequence, $r_u^{(1)}$ is obtained as

$$r_u^{(1)} = \left(r_u^{(1)}(1)\,, r_u^{(1)}(2)\,, r_u^{(1)}(3)\,, \ldots, r_u^{(1)}(n) \right), \quad \forall n \geq 4 \tag{3}$$

where

$$r_u^{(1)}(k) = \sum_{i=1}^{k} r_u^{(0)}(i), \qquad k = 1, 2, 3, \ldots, n, \tag{4}$$

which results in the grey differential equation given as

$$\frac{dr_u^{(1)}(t)}{dt} + a r_u^{(1)}(t) = b. \tag{5}$$

The coefficients, a and b, can be obtained by using least square method, as shown in (6):

$$[a, b]^T = \left(B^T B \right)^{-1} B^T Y, \tag{6}$$

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where

$$Y = \left[r_u^{(0)}(2)\,, r_u^{(0)}(3)\,, \ldots, r_u^{(0)}(n)\right]^T,$$

$$B = \begin{bmatrix} -z^{(1)}(2) & 1 \\ -z^{(1)}(3) & 1 \\ . & . \\ . & . \\ -z^{(1)}(n) & 1 \end{bmatrix}, \tag{7}$$

and $z^{(1)}(k) = \alpha r_u^{(1)}(k) + (1-\alpha)\, r_u^{(1)}(k-1)\,,\ k = 2, 3, \ldots, n$, α is the weighting factor.

Once a and b in (5) are obtained, the grey differential equation can be used to predict the value of r_u at time instant $k+1$.The solution of $r_u^{(1)}(t)$ at time $k+1$, i.e. the AGO grey prediction model is expressed as

$$\hat{r}_u^{(1)}(k+1) = \left[r_u^{(0)}(1) - \frac{b}{a}\right] e^{-ak} + \frac{b}{a}, \quad k = 0, 1, \ldots \tag{8}$$

Consequently, the prediction value of the benchmark RSRP data at time $(k+1)$ can be calculated by an IAGO as

$$\hat{r}_u^{(0)}(k+1) = \left[r_u^{(0)}(1) - \frac{b}{a}\right] e^{-ak}\,(1 - e^{a}) \tag{9}$$

2) Grey Prediction Modification Using Fourier Series of Residual Error: According to [16] grey model prediction accuracy can be improved by the Fourier series of error residuals. Consider the u^{th} user RSRP sequence, $r_u^{(0)}$ in (2) and its predicted values obtained from (9), then the error of the sequence $r_u^{(0)}$ can be expressed as

$$\xi_u^{(0)} = \left(\xi_u^{(0)}(2), \xi_u^{(0)}(3), \ldots, \xi_u^{(0)}(n)\right), \tag{10}$$

where

$$\xi_u^{(0)}(k) = r_u^{(0)}(k) - \hat{r}_u^{(0)}(k), \forall k = 2, 3, \ldots, n. \tag{11}$$

The error residuals given in (11) can be re-expressed in Fourier series in the following approximation

$$\xi_u^{(0)}(k) \approx \frac{1}{2}a_0 + \sum_{i=1}^{V}\left[a_i \cos\left(\frac{2\pi i}{T}k\right) + b_i \sin\left(\frac{2\pi i}{T}k\right)\right], \tag{12}$$

$\forall k = 2, 3, \ldots, n$, where $T = n-1$ and $V = \lfloor \frac{n-1}{2} \rfloor - 1$. Note that the expression in (12) further be re-expressed as

$$\xi_u^{(0)} \approx Q\mathcal{C}, \tag{13}$$

where

$$Q = \begin{bmatrix} 0.5 & \cos\left(2\frac{2\pi}{T}\right) & \sin\left(2\frac{2\pi}{T}\right) & \cos\left(2\frac{2\pi 2}{T}\right) & \sin\left(2\frac{2\pi 2}{T}\right) & \ldots & \cos\left(2\frac{2\pi V}{T}\right) & \sin\left(2\frac{2\pi V}{T}\right) \\ 0.5 & \cos\left(3\frac{2\pi}{T}\right) & \sin\left(3\frac{2\pi}{T}\right) & \cos\left(3\frac{2\pi 2}{T}\right) & \sin\left(3\frac{2\pi 2}{T}\right) & \ldots & \cos\left(3\frac{2\pi V}{T}\right) & \sin\left(3\frac{2\pi V}{T}\right) \\ \ldots & \ldots & \ldots & \ldots & \ldots & \ldots & \ldots & \ldots \\ 0.5 & \cos\left(n\frac{2\pi}{T}\right) & \sin\left(n\frac{2\pi}{T}\right) & \cos\left(n\frac{2\pi 2}{T}\right) & \sin\left(n\frac{2\pi 2}{T}\right) & \ldots & \cos\left(n\frac{2\pi V}{T}\right) & \sin\left(n\frac{2\pi V}{T}\right) \end{bmatrix}$$

and $$\mathcal{C} = \begin{bmatrix} a_0 & a_1 & b_1 & a_2 & b_2 & \ldots & a_n & b_n \end{bmatrix}^T \tag{14}$$

Hence, $\mathcal{C}$ can be obtained by using the least square method to solve (13) as

$$\mathcal{C} = \left(Q^T Q\right)^{-1} Q^T \xi_u^{(0)}. \tag{15}$$

The Fourier series correction is thus given according to [16] as

$$\hat{\hat{r}}_u^{(0)}(k) = \hat{r}_u^{(0)}(k) - \hat{\xi}_u^{(0)}(k), \forall\ k = 2, 3, \ldots, n+1 \tag{16}$$

TABLE I
SIMULATION PARAMETERS.

Parameter	Value (units)
Data BS Transmit Power	10 dBm
Control BS Transmit Power	46 dBm
Channel Model	Urban Outdoor
Pathloss Model	[18]
Minimal sensible signal strength	-105.5 dBm
Shadowing standard Deviation	$2-12$ dB
Shadowing Correlation	0.5 between cells
Shadowing Correlation Distance	25 m
Waypoint model speed interval	$[0, 10]$ m/s
Waypoint model pause time interval	$[0, 1]$ s
Waypoint model walk interval	$[2, 6]$ s
Detection threshold μ	0.5
Detection window size N	10
Grey weighting factor α	0.5

3) Outage Decision: Firstly, the RSRP of all the UTs that were previously attached to the data BS whose outage is been detected, i.e., data BS, d, are predicted according to (9) or (16). Then for each UT the control BS compares its predicted RSRP value, $v_u = \hat{r}_u^{(0)}(k+1) \approx \hat{\hat{r}}_u^{(0)}(k+1)$, with the RSRP after the trigger, $r_u = r_u^{(0)}(k+1)$. If after the outage trigger, the UT, u, is been served by the control BS for data transmission and $v_u = \hat{r}_u^{(0)}(k+1) \approx \hat{\hat{r}}_u^{(0)}(k+1) > r_u - \Delta$, where Δ is the data cell range expansion offset, the counter, i_1, is incremented by 1, since the UT should be associated with data BS, d, based on the prediction. Otherwise, the counter, i_2 is incremented by 1. On the other hand, if another data BS is serving UT u, after the outage trigger and $v_u \approx \hat{r}_u^{(0)}(k+1) \approx \hat{\hat{r}}_u^{(0)}(k+1) > r_u$, the counter, i_1, is incremented by 1, otherwise an inverse prediction is performed on the RSRP to the serving data BS. The inverse prediction checks the RSRP to the data BS d and RSRP to the serving data BS after the trigger, i.e. data BS $\bar{d}$, at the point just before the trigger. The control BS waits for the prediction window size, N, and performs an inverse prediction on the RSRP of each of the UTs associated with data BS $\bar{d}$ to obtain the predicted RSRP prior to the trigger decision, iv_u. Thus if the RSRP of the u^{th} UT to the serving data BS (d) before trigger, ov_u, is such that $ov_u > iv_u$ the counter i_1 is incremented by 1 otherwise, the counter i_2 is incremented by 1.

Finally, an outage is declared if the ratio $\frac{i_1}{i_1+i_2} > \mu$, where μ is a predefined threshold.

IV. SIMULATION RESULTS AND DISCUSSION

In this section, we demonstrate the performance of our data cell outage detection scheme and the impact of the system parameter on the detection accuracy with simulation results.

A. Simulation Setup

We consider a heterogeneous cellular architecture with several small cells overlaid on a macrocell. The small cells are distributed randomly within an area of 1 km $\times$ 1 km. The control and data BS operates on separate carrier frequency with each having a 10 MHz channel bandwidth. The UTs are distributed randomly within the coverage area. We assume a small cell range expansion offset of 12 dB, which means

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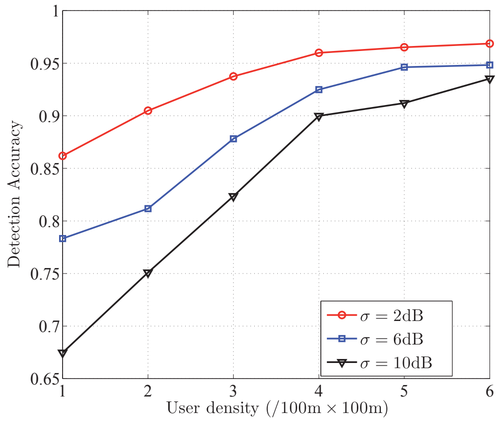

Fig. 3. *Performance of data cell outage detection scheme*

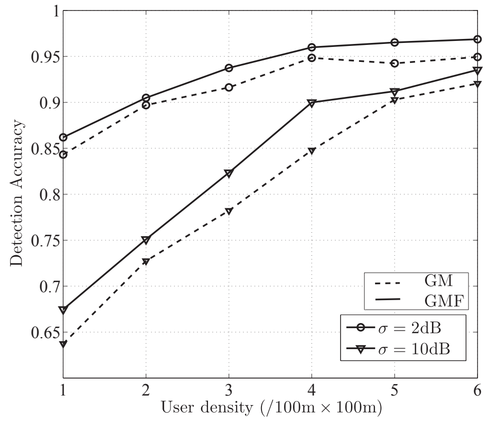

Fig. 5. *Comparison of the performance of GM and GMF*

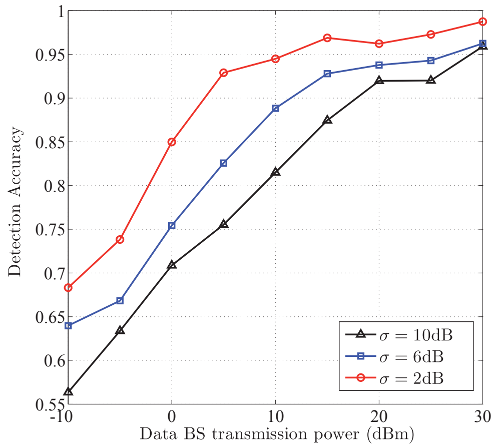

Fig. 4. *Effect of data BS transmission power on detection accuracy*

that a UT will be associated with the small cell for data transmission even if its RSRP value is 12 dB weaker than the control BS [19]. Otherwise, the UT will be associated with the control BS for both data transmission and control signalling. All small cells use a uniform transmission power. Each UT move according to the random waypoint mobility model within the coverage area of the network [20]. Also, the UTs send their data BS RSRP report to the control BS every 0.1 s. Unless otherwise stated, the number of data BS, $M = 100$, while the remaining system parameters are given in Table I. The simulation results are the average results from 1000 randomly generated network topologies.

B. Overall Performance

Figs. 3, 4 and 5 illustrates the overall performance our data cell outage detection, i.e., the detection accuracy. The detection accuracy is the probability of accurately detecting an outage data cell. In Figs. 3 and 4, we utilized the grey prediction modification with Fourier series of residual error (GMF) to plot the detection accuracy against the user density and the data BS transmission power, respectively, for shadowing fading standard deviation of, $\sigma = 2, 6$ and 10dB. Fig. 3 clearly shows that increasing the user density increases the detection accuracy. This is due to the fact that increasing user density enables a better spatial correlation. Fig. 4 depicts the detection accuracy for various data BS power levels and a user density of $3(/100\text{m} \times 100\text{m})$. The result shows that low data BS transmission power results in degradation of the detection accuracy, while increasing the transmission power leads to an improvement in the detection accuracy. This is because when the data BS transmission power increase, it becomes easier to distinguish between the predicted RSRP statistics of the outage case and normal case. In Fig. 5, we compared the performance of the grey prediction model (GM) and the Fourier modified version (GMF) which are obtained from (9) and (16), respectively. We observe that the GMF scheme outperforms the GM as expected, since the former utilizes the prediction error in the later to improve its performance. It can also be observed in Figs. 3, 4 and 5 that the detection accuracy is lower with larger shadowing fading standard deviation σ. This is because a high σ means a severe shadowing fading, which leads to a more random RSRP statistic.

Fig. 6, investigates the impact of the predefined threshold μ on the detection accuracy, by using the GMF approach, for various user densities in $(/100\text{m} \times 100\text{m})$ and $\sigma = 6$ dB. It can be seen that the highest detection accuracy is obtained by setting $\mu = 0.5$. This setting implies that the RSRP prediction of more than half of the UTs that were associated with the data BS whose outage is been detected, i.e. d, must indicate the existence of an outage, before d can be declared to be in outage. The stepwise shaped plot is obtained since the number of UTs must be an integer value. It can also be seen that no much degradation in detection accuracy is obtained until $\mu > 0.67$, which implies more than two-third of UTs that were associated with d must indicate the existence of an outage.

Fig. 7, investigates the impact of the prediction window size N on the detection accuracy, by using the GM approach, for $\sigma = 2, 6$ and 12dB and a user density of $3(/100\text{m} \times 100\text{m})$. It can be observed that increasing the prediction window size above the require minimal $(N = 4)$ leads to an increase in detection accuracy up to a given point where any further increase in N has no impact on the detection accuracy. Fig. 7 further

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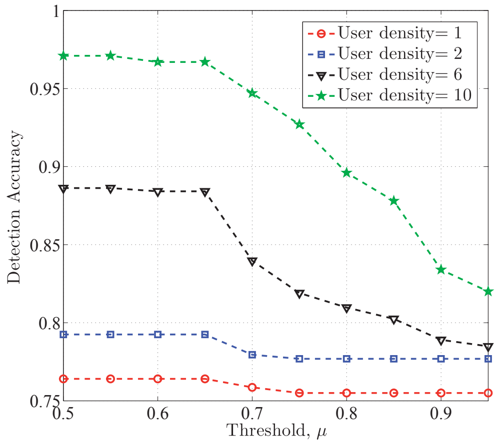

Fig. 6. *Effect of threshold setting on detection accuracy*

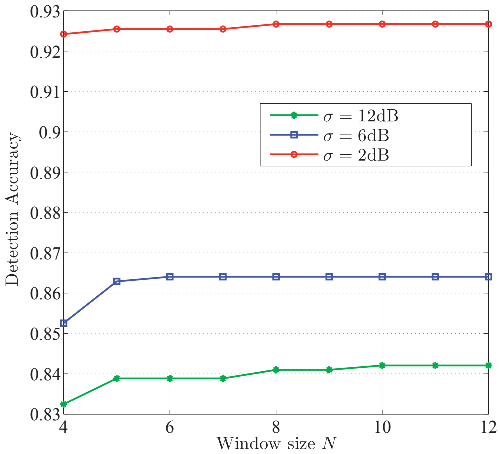

Fig. 7. *Effect of window size on detection accuracy*

shows that increasing N has more impact on the detection accuracy for larger shadow fading standard deviation, σ. This is because of the lower randomness in RSRP statistics when σ is low; hence a low value of N is required to obtain the highest attainable detection accuracy which is the contrary for higher σ where a higher value of N is required.

V. Conclusion

This paper proposes a data cell outage detection scheme for the HetNets with separated control and data plane functionalities. Our outage detection process is subdivided into the outage trigger phase and outage detection phase. The outage trigger phase leverages on the ability of the control BS to monitors the UT-data BS association and therefore triggers outage detection when irregularities in the association occurs. In the detection phase, we utilize the grey prediction model to determine the occurrence of an outage. Our evaluations show that our data cell outage detection scheme achieves a high detection accuracy.

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