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Efficient Performance Monitoring for Ubiquitous Virtual Networks Based on Matrix Completion

XINHENG WANG[1], CHUAN XU[1], (Member, IEEE), GUOFENG ZHAO[1], KUN XIE[2], (Member, IEEE), AND SHUI YU[3], (Senior Member, IEEE)

[1]School of Communication and Information Engineering, Chongqing University of Posts and Telecommunications, Chongqing 400065, China
[2]College of Computer Science and Electronics Engineering, Hunan University, Changsha 410006, China
[3]School of Information Technology, Deakin University, Burwood, VIC 3125, Australia

Corresponding author: Chuan Xu (xuchuan@cqupt.edu.cn)

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ABSTRACT Inspired by the concept of software-defined network and network function virtualization, vast virtual networks are generated to isolate and share wireless resources for different network operators. To achieve fine-grained resource control and scheduling among virtual networks (VNs), network performance monitoring is essential. However, due to limitation of hardware, real-time performance monitoring is impossible for a complete virtual network. In this paper, taking advantage of the low-rank characteristic of 90 virtual access points (VAPs) measurement data, we propose an intelligent measurement scheme, namely, adaptive and sequential sampling based on matrix completion (MC), which exploits from the MC to construct the complete data of VN performance from a partial direct monitoring data. First, to construct the initial measurement matrix, we propose a sampling correction model based on dispersion and coverage. Second, a stopping condition for the sequential sampling is introduced, based on the stopping condition, the sampling process for a period can stop without waiting for the matrix reconstruction to reach certain of accuracy level. Finally, the sampled VAPs are determined by referring the back-forth completed matrixes' normalized mean absolute error. The experiments show that our approach can achieve a constant network perception and maintain a relatively low error rate with a small sampling rate.

INDEX TERMS Performance monitoring, low-rank, matrix completion, adaptive.

I. INTRODUCTION

Wireless network virtualization (WNV), an integration of Software-defined network (SDN) and Network Function Virtualization (NFV) technologies, has become one of the main trends in wireless systems. WNV abstracts the physical resources (e.g., network infrastructure, backhaul, licensed spectrum, core and radio access network [RAN], energy/power etc.) to a number of virtual resources, and facilitates common resource sharing among different network operators and consumers [1], [2].

Based on the real-time performance monitoring (e.g., traffic, signal strength) on ubiquitous virtual networks (VNs), high resource utilization, better quality-of-experience (QoE) and easier migration can be provided for end users [3]. However, performance monitoring is very difficult for every virtual network in complex heterogeneous deployments [4]. This is mainly reflected in two aspects. First, a large number of virtual networks are created that are much larger than the traditional network, meanwhile, have brought additional consumption of I/O, storage and processed resources on wireless devices [5]. Second, as shown in Fig. 1, when a user migrates from one type of network to another during the walk, it is difficult to monitor performance indicators which can provide handover strategy in real-time [6]. Moreover, to support multi-connection for multi-path transmission, it is responsible for monitoring the parameters of the application layer and network layer.

To address the problems mentioned above, two main technical challenges should be considered. First, to reduce the network cost, we must precisely take partial measurement samples from the data, rather than taking all samples together; second, to enhance the accuracy of estimation and improve

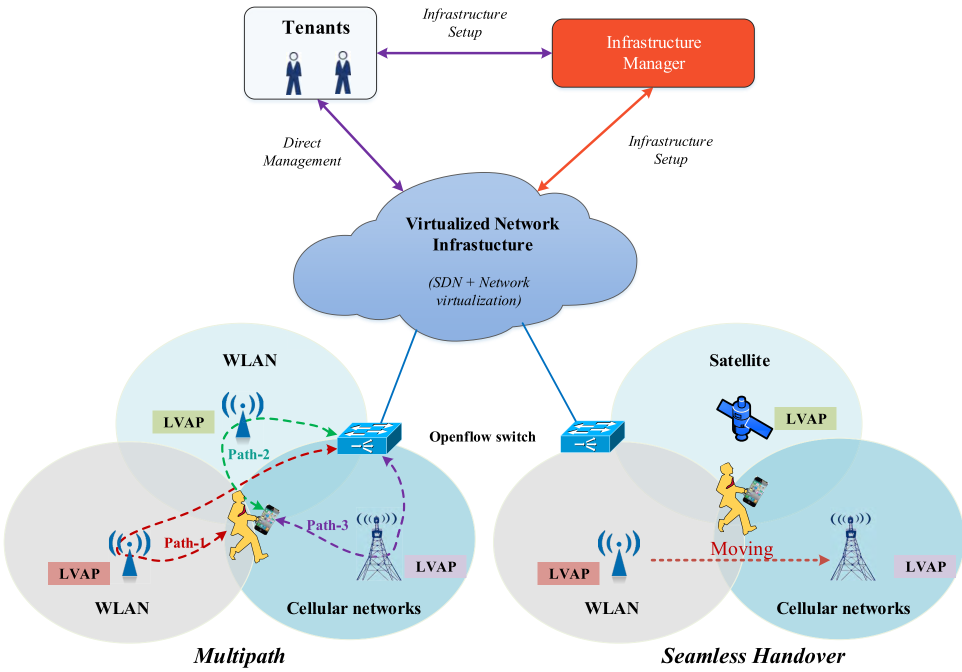


Fig. 1. By using open interfaces and protocols to programmatically control network elements, a user can be migrated seamlessly and multipath-supported transmission can be achieved in real-time in heterogeneous network.

the self-adaption of the scheme in dynamic environments, we need to repeatedly learn the behavior of the measured results in real-time.

In order to minimize the measurement points, the pervasive use of samples can be extracted from the network-wide. In 1989, the idea of probability and mathematical statistics of sampling was introduced into the network measurement. But it is impractical to learn the complete network information with a subset of samples. The availability of the Nyquist sampling theory offers new opportunities for reconstruction matrix, which can recover the whole condition with partial measurements. When the number of measurements increases higher than the Nyquist sampling rate, Compressive Sensing (CS) is proposed to reconstruct sparse signals. Nguyen and Teague [7] integrate between CS and clustering methods to collect data that significantly reduce power consumption for the networks. However, since VAP's network performance has unique patterns, CS cannot be directly applied to gain notable accuracy. Matrix Completion (MC) as the evolution of CS technology provides a new perspective for data gathering in wireless sensor networks with benefits of high accuracy and practicality [8]. By fully exploiting the low-rank and sparse nature of readings among sensor nodes, Malboubi *et al.* [9] proposes an energy efficient manner to gather data based on MC and CS. An on-line weather data gathering scheme is proposed based on MC theory, which can adaptively sample different locations according to environmental and weather conditions [10].

Note that, existing MC-based data gathering solutions are only applied with an assumption that the sensed data has a constant rank. However, the rank of the matrix is dynamicly changing due to unstable and time-varying network conditions during the on-line monitoring of a practical environment. Our solution is highly inspired by Xie *et al.* [11] who proposes an adaptive monitoring systems based on MC. We analyze the characteristic of 90 VAPs' measurement data, which reveals the features of low-rank. Motivated by this finding, we seek effective use of MC to complete the measurement. According to the theory of MC, if the rank varies, real-time sampling set will be required to achieve recovery.

Aiming to realize a controllable measurement for all the VAPs, we propose VAP's three performance indicators measuring method respectively based on libpcap open source library, Netlink mechanisms and OpenFlow protocol including signal strength, the number of associated Users and Traffic (SUT). In order to solve the problem of recovering from a small number of real-time measurement data to obtain the whole network data set, a method of Adaptive and Sequential Sampling based on Matrix Completion (MC-ASS) is proposed, based on few VAPs' direct measurements, MC-ASS algorithm uses matrix completion recovery method for estimating the other virtual AP's corresponding performance value. We propose a sampling correction model based on dispersion and coverage during sampling initiation, which can avoid the same location sampling in adjacent time slots. Furthermore, we propose an adaptive sampling strategy to identify the sampling set by calculating the reconstruction error until it reaches the accuracy requirement. The real-world experiments show that our scheme can maintain a relatively low error-rate while minimizing network resource consumption. The detailed contributions are as follows.

- By mining the large datasets in real measurement data collected, a good feature of low-rank is revealed. Based on these observations, an online data collection framework for ubiquitous virtual networks is designed by exploiting MC techniques for estimating the non-observed data.
- To construct the initial measurement matrix, we propose a sampling correction model based on dispersion and coverage. Compared with other models, our model ensures that the matrix has better features for higher MC performance.
- Instead of random sampling, we design a more intelligent sampling strategy, which can choose the sample node set with adaptive methodology based on the back-forth completed matrixes' normalized mean absolute error until it achieves a reasonable recovery accuracy.
- Finally, we implement our virtual network measurement scheme in an SDWN system and deploy it in real network of our campus to evaluate its performance. The experimental results demonstrate that our scheme can reconstruct the complete matrix with required precision by only a third of the total VN data.

The remainder of the paper is organized as follows. In section II, we give an overview of the related work. We present the fundamentals of MC theory, and discuss the existing problems in section III. In section IV, we analyze the characteristics of matrix rank. We illustrate the implementation details of MC-ASS in section V. Section VI shows the experimental evaluation. Finally, the paper is concluded in Section VII.

II. RELATED WORK

We review the related work and identify the differences between our research and existing research.

A. TRAFFIC MEASUREMENT

Recently, Yassine *et al.* [12] described current trends and challenges about the traffic measurement methods in SDNs, in terms of real-time and flexibility is weak. In fact, traffic measurement in SDNs is still in its infancy stage, further research is required to provide effective measurement scheme.

There had been some studies on leveraging SDN in wired network, and the most relevant work is iSTAMP [13]. However, iSTAMP faced aggregation feasibility issues in practical implementation and only focused on single-switch scenario. While the Gong *et al.* [14] focused on accurate and feasible traffic matrix estimation approaches by extending iSTAMP framework. A similar approach is described in [15] designed a traffic matrix estimator by keeping track of statistics for each flow in OpenFlow switches, called OpenTM. In [9], an intelligent network measurement framework was designed which can be applied to a variety of network performance measurements via applying MC techniques. Given the network measurement and inference, Liu *et al.* [16] performed adaptive measurement with online learning. When it comes to the wireless networks, a recent work [17] proposed a software defined wireless measurement architecture called TinySDM, which defined a set of carefully selected hooks that allowed multiple measurement tasks.

Due to the difficulty of deployment, existing methods are hard to be used in practical. In our work, we propose a framework to leverage the global view of SDN controller, then the direct measurement points of the whole network can be determined through the continuous online learning.

B. DATA RECONSTRUCTION

The intractable plights that the future network architecture is becoming large-scale, it will be costly and operationally difficult for users to monitor the properties of all links due to the strict energy limitation and the common vulnerability of wireless environment. The common measurement strategy usually takes random samples nodes from the full traffic data, which will result in the partial missing or non-observed data. Inspired by the great convenience offering by Nyquist sampling theorem, several works (e.g., CS, MC) have been studied to address the data reconstruction [18].

CS is a powerful and generic technique for reconstructing matrix, which requires the data containing the features of sparse/low-rank. By the specific feature of sparsity, Wang *et al.* [19] propose an adaptive data gathering scheme based on CS, which performs badly for large-scale WSNs. In [20], a random walk algorithm is proposed, which allows to collect measurements for CS along random routing paths. Note that sparsity is the guarantee of accurate reconstruction of measured data in CS theory, but most applications in the real scenarios do not have obvious sparsity features.

Building on ideas of CS, MC which has emerged very recently is a more efficient data gathering method. The work in [21] is the state-of-the-art MC based data gathering scheme which utilizes the low-rank and short-term stability features in WSNs to achieve both reduced data traffic and high level of recovery accuracy based on MC techniques. A similar approach is described in [11], this paper proposes a MC-based weather data recovery scheme by identifying the successive data corruption, which can achieve very high recovery accuracy in the presence of successively missing and corrupted data. However, traditional work usually assumes that the rank is known and stable, only the research in [22] tries to study data gathering in a dynamic network environment, which highly inspired our solution.

Recently, the idea of MC has been introduced into SDN's measurement. Polverini *et al.* [23] enhances the traffic matrix estimation by utilizing SDN concept. So as to get accurate and efficient network-wide traffic, the work in [16] integrates SDN and MC to perform adaptive measurement with online learning. The same scheme is adapted in [9], Malboubi leverages the flexibility provided by SDN to design the optimal observation or measurement matrix that can achieve the best estimation accuracy using MC techniques.

The proposed MC-ASS scheme builds upon the recently proposed framework of the MC techniques. The scheme provides a more practical approach, which relaxes the traditional MC theory in a fix rank and allows to collect measurements in a dynamically changing rank.

III. PRELIMINARY AND PROBLEM FORMULATION

In this section, the fundamentals of matrix completion is introduced. We also describe the problem need to be solved in the existing measurement schemes.

A. FUNDAMENTALS OF MC

We give some preliminarys of MC. Based on the low rank MC theory, which considers recovering the incomplete data matrix by observing a small part of the matrix elements [24], [25]. Let $X \in R^{n_1 \times n_2}$ be an unknown matrix with rank $r << \min\{n_1, n_2\}$. If a subset of its entries $(i, j) \in \Omega$ are known, the subset Ω is formed with randomly selected entries of the matrix and the sampling operator $P_\Omega : R^{n_1 \times n_2} \longrightarrow R^{n_1 \times n_2}$ is defined by:

$$[P_\Omega(X)]_{ij} = \begin{cases} X_{ij} & (i, j) \in \Omega, \\ 0 & otherwise. \end{cases} \tag{1}$$

If the set Ω has enough information and the low-rank structure problem can be achieved through solving a minimization problem.

$$\begin{aligned} &\min \ rank(X), \\ &s.t. \ P_\Omega(X) = P_\Omega(M), \end{aligned} \tag{2}$$

where rank(.) denotes the rank of a matrix. However, solving this rank minimization problem in (2) turns out to be the convex optimization problem because it is NP-hard. Hence people tend to consider its relaxation:

$$\begin{aligned} &\max \ \|X\|_*, \\ &s.t. \ P_\Omega(X) = P_\Omega(M). \end{aligned} \tag{3}$$

Here, $\|X\|_*$ is the nuclear norm of the matrix $\|X\|_* = \sum_{i=1}^{r} \delta_i(X)$, which is the sum of its singular values. Intuitively, it's a question of semidefinite programming.

In order to recover the full matrix, Candes [26] pointed out that m should be met with the restricted condition (4).

$$m \geq C n^{6/5} r \log n, \tag{4}$$

where C is a constant value.

B. PROBLEM DESCRIPTION

In order to measure and analyze the real-time network performance of large-scale, as is shown in Fig. 2, the traditional measurement scheme is to directly measure all nodes of VAP. In these scenarios, all the nodes of the network result in substantial increase in load consumption and high sensing cost. Furthermore, the measurement results will not only consume storage resources but also take up network bandwidth when they are uploaded to the Controller. It is impractical due to the strict network resource limitation.

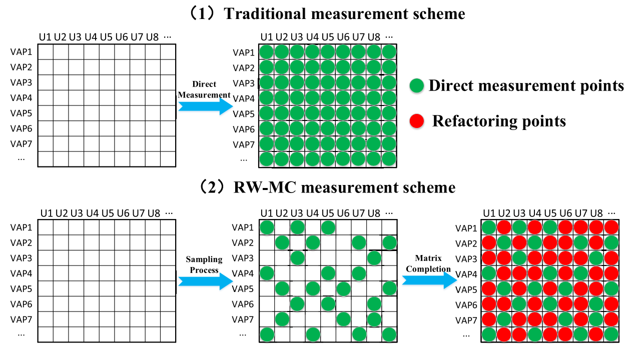


Fig. 2. The traditional measurement scheme VS MC-ASS measurement scheme.

Involuntarily, for the sake of reducing the the waste of resources, some conventional technologies are deployed, such as distributed source coding techniques, and clustered data aggregation. However, These methods are not suitable for the dynamic environment.

An effective way to reduce the energy consumption of energy constrained wireless sensor network is reducing the number of collected data, which causes the problem that how to recover missing values from the partial direct measured. Furthermore, simply choosing the random sample can hardly meet the accuracy demands. Our goal is to efficiently schedule the data collection process to significantly reduce the sensing resources needed while maintaining the sensing quality.

C. PROBLEM FORMULATION

To better understand the problem, we take signal strength as an example of network performance for a detailed description, and then propose our solutions. This method will help to apply the theory to various network performance monitoring.

Suppose there are N VAPs, and the number of mobile terminals in a certain time period is M. Define $X_{N\times M}$ as the signal strength matrix, the VAP as the row of the matrix, and STA as the column of the matrix, where the X_{ij} represents the signal strength of the ith VAP in the matrix X and the jth STA. Before introducing our solutions, we give two definitions for easily presenting the theorem.

We use a Binary Sample Matrix, $\vec{B}(t)$: $\vec{B}(t) \in R^N$ to show whether the entries are non-observed. If the measurement points are selected, nonzero is marked, otherwise, we use zero as a placeholder to replace the empty entry.

$$B = (B_{ij})_{N\times M} = \begin{cases} 1 & Direct\ Measurement, \\ 0 & Otherwise. \end{cases} \tag{5}$$

We seek to estimate non-observed data based on the partial direct measurements.

Incomplete sensory matrix $M_{N\times M}$

$$M_{N\times M} = X_{N\times M} \bullet B_{N\times M}. \tag{6}$$

In (6), $\bullet$ is representation of inner product operation. Based on matrix theory described in Section II(V), when the number of samples is more enough and meets the conditions (4), the matrix $X_{N\times M}$ can be reconstructed from sensory matrix $M_{N\times M}$ by solving the following problem

$$\begin{aligned} &\min \ \|X\|_*, \\ &s.t.\ X_{ij} = M_{ij}, \\ &\quad M_{N\times M} = X_{N\times M} \bullet B_{N\times M}. \end{aligned} \tag{7}$$

Obviously, the matrix $B_{N\times M}$ denotes which VAP needs to take samples. In order to minimize the cost of the network, the optimal should be considered.

We give the basic idea of our approach using MC technologies. In fact, the proposed MC-ASS consists of two phases: the learning phase and the measurement phase in Fig. 3. The learning phase means to figure out the numbers of samples and the direct measurement points with the MC-ASS algorithm. In measurement phase, the Controller periodically reads traffic counters from the learning phase and estimates the traffic matrix.

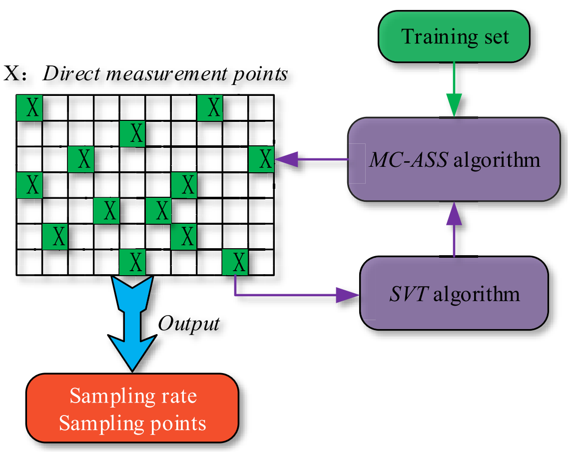


Fig. 3. The process of MC-ASS measurement scheme.

D. CHALLENGES

In order to make the matrix reconstruction reach a certain accuracy level, some problems should be considered in the implementation of MC-ASS, namely, when and how the matrix can be reconstruction based on the known data. We conclude the challenges as the following aspects:

- Based on the theory of MC, it is difficult to confirm how many samples are sufficient to satisfy the matrix reconstruction conditions due to the constantly changing rank in real-time network monitoring.
- The measured points are chosen not randomly but through an intelligent strategy. However, without a prior knowledge of the matrix structure, designing such a sampling strategy is very hard.

Note that, the low-rank is the prerequisite for using MC. Before we present our data collection algorithm, we first analyze a large set of monitoring data to better understand the characteristics of network performance in the next section.

IV. MEASUREMENT DATA MINING

In this section, we first propose the layered architecture, and then describe our approach to efficient datasets gathering. To check whether the data matrix has a good low-rank approximation, the features of datasets are thoroughly analyzed.

A. DATA SETS

A flexibility measure framework for network analysis is necessary, especially, numerous emerging network architectures and protocols have triggered the demand for network measurement [27]. Benefit from the application of SDN and NFV, Fig. 4 gives an overview of Software-defined Wireless Network (SDWN) measurement architecture which mainly includes Controller, AP Agent Daemon and Open vSwitch (OVS). Each of the components will be presented in detail in the following sections.

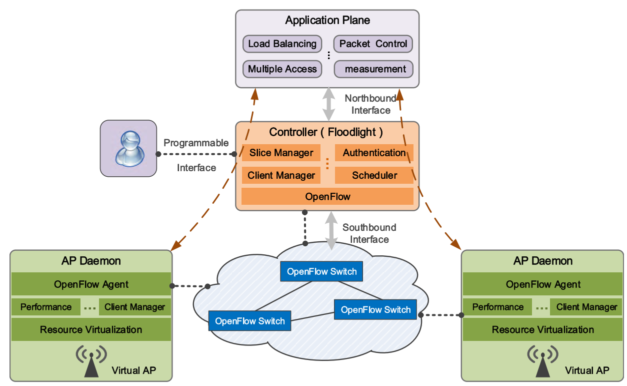


Fig. 4. SDWN measurement framework.

1) MEASUREMENT FRAMEWORK

a: CONTROLLER

The Controller is a software which runs on a centralized server. As an SDN controller, which provides a set of interfaces (the northbound interface) to the applications and translates their requests into a set of commands (the southbound interface) to the network executing devices. Network applications (seamless handover, load balancing) execute as a thread on the Controller, which are easy to design and modify. Controllers can use southbound API to obtain information about capacity and demand from the underlying devices, and set up forwarding policy. The Controller needs monitor and analyze module uses the information gathered from the OVS and AP Daemon by using the openflow protocol. This reporting is one of the key components allowing controllers to take decisions, such as mobility handover, load balancing strategy.

b: AP DAEMON

AP Daemon runs on the physical APs, executes the command from the Controller to orchestrate the wireless network, measures and reports the performance of Clients on APs. As the measurement system of execution module, it sniffers the wireless frames in real time for monitoring the performance, to support a publish-subscribe information system when a certain measurement task is triggered.

c: OVS

OVS [28] is a popular software switch widely employed by SDN. OVS runs on AP and acts as the bridge module. It includes: one wireless interface belonging to the Wireless Mesh Network (wlan0); an optional wired interface towards client Access Networks (eth0); a virtual interface br0, which is a software bridge using OpenFlow switching logic.

2) DATA COLLECTION

In literature, a huge amount of work [29]–[32] shows that monitoring and analyzing real-time network traffic is very useful for decision-making in Controller. In the SDWN framework, we make it possible to achieve the data collection of three major performance indicators, including the AP signal strength, the number of associated users and data flow, through the traditional AP equipment software and libpcap, Netlink, Open vSwitch and other technology applications. At the same time, the MC-ASS algorithm running on the application plane handles the AP data collected by the controller through the API and instructs API to issue the data acquisition instruction. The acquisition of the whole network AP performance data are realized in the final, and recorded in the database. In this experiment, there are 90 virtual AP nodes in the SDWN test bed, in which the number of mobile terminals is the actual number of users in the scenario. We have recorded data reading from the Controller with a time granularity 20 seconds. The dataset spans a duration of nearly one month.

B. THE CHARACTERISTICS OF MATRIX RANK

From the theory of MC, low-rank is the cornerstone of MC. Through an in-depth analysis of the real datasets, we verify whether the monitoring matrix has a good low-rank structure. Any $i \times j$ matrix X can be decomposed into three matrices using Singular Value Decomposition (SVD), as shown in the type (8):

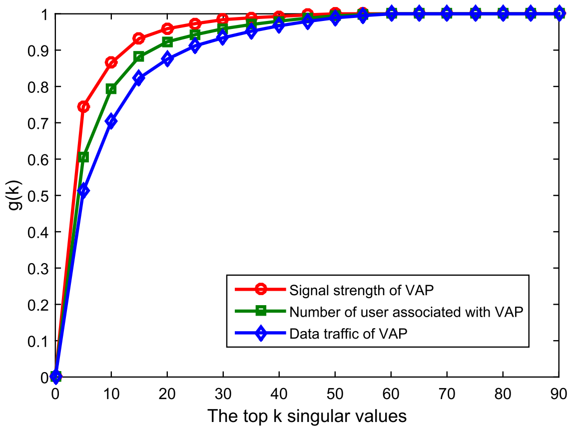
$$X = U \sum V^T, \tag{8}$$

where U is an $N \times N$ unitary matrix, V is an $N \times N$ unitary matrix, and $\sum$ is an $N \times N$ diagonal matrix with diagonal elements organized in decreasing order.

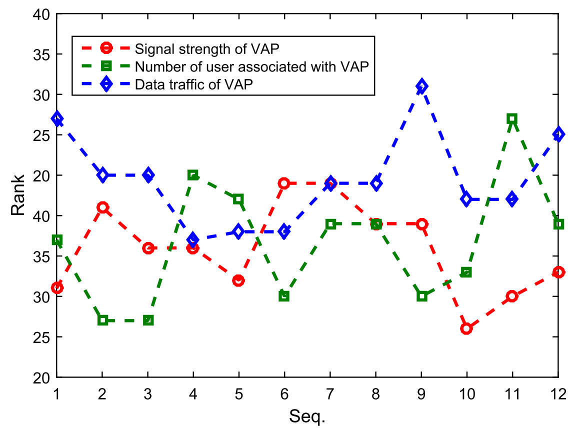
If a matrix has low-rank, its top K singular values occupy the total or near-total energy. In order to verify whether the VAP data traffic matrix has low rank, define functions expression is:

$$g(K) = \frac{\sum_{i=1}^{K} \delta_i^2}{\sum_{i=1}^{r} \delta_i^2}. \tag{9}$$

Fig. 5(a) plots the fraction of the total variance captured by the top k singular values. It is observed that the top 20 singular values capture 70%-90% variance in the real traces. These results indicate that the data matrix X has a good low-rank approximation in all the scenarios under investigation.



(a)



(b)

Fig. 5. The matrix rank of dynamic change. (a) Low-rank feature. (b) Temporal stability feature.

In order to better investigate the characteristics of rank, Fig. 5(b) shows the rank of top twelve measurement matrices. The X-axis is the ordinal number of the measurement matrix, and the Y-axis is the rank of the corresponding matrix. Obviously, the rank does not have a constant rank, so the number of samples that needs to take should adapt accordingly.

V. MEASUREMENT SCHEME

In this section, the implementation details of MC-ASS include four strategies. Firstly, to construct the initial measurement matrix, we propose a sampling correction model based on dispersion and coverage. Secondly, benefiting from the features of VAP's network performance, the clustering operation is firstly performed. Thirdly, we propose a sampling stopping condition for determining the nodes to be measured. Finally, we predict the sampling set by comparing normalized difference values between two consecutive time slots.

A. INITIALIZE THE MEASUREMENT MATRIX

In the training phase, we suppose the number of VN nodes is N and the user is M. The initial measurement matrix can be denoted as $X_{N \times M}(t)$, and the rank of the matrix is

$r = rank(X_{N\times M}(t))$. Therefore, the number of samples m of the matrix can be calculated according to $m \geq Cn^{6/5} r \log n$. From Section V, since the initial matrix determines the RW process, the distribution of samples has great influence on the accuracy of reconstruction. To successfully apply the MC techniques, the initial sampling matrix is constrained to have at least one samples in each row and column, which should have an appropriate interval bounds.

To fend off the obstacle, a great deal of existing work has been done. In [33], the authored analyze two models to obtain the sample set, the Bernoulli model and the Uniform model. The former is generally designed for a particular test scenario which lacks flexibility. In this model, each entry has same probability that is $p = m/(N \times M)$. The latter assumes that Ω is sampled uniformly at random among all subsets of cardinality m. However, due to the temporal stability of sampling data, the desired sampling principle should avoid sampling the same location in adjacent time slots. To overcome this limitation, in [10] proposed a cross sampling principle so that the sampling has different location in adjacent time slots.

In contrast, instead of gathering data through uniform sampling, we come up with a novel rule which can avoid parameter tuning and guarantee the matrix to have better feature for higher matrix completion performance. Based on dispersion and coverage, the effective sampling set can be determined.

The details of algorithm is show in Algorithm 1, we use tau_i and tau_j to denote the standard deviation threshold of AP number and time slot number. The two values have strong correlation with the size of the data matrix and we obtain them through the training for large times. In step 3, when a random sampling result can't meet the requirement of the threshold, we consider that the sampling result is not widely distributed in the data matrix and go back step 1 to resample. Meanwhile, In order to reconstruct the matrix, the samples should avoid a row or a column being un-sampled which will cause matrix completion failure. When these two conditions are satisfied, we consider the samples of initial sliding window data matrix are reliable and efficient.

The model takes the dispersion and the coverage, which yield a better guide for the adaptive sampling strategy into consideration. Thus, according to the samples and Singular Value Thresholding (SVT) matrix reconstruction algorithm, we calculate the reconstruction error rate as the benchmark reconstruction error which is used in the adaptive sampling algorithm.

Algorithm 1 Sampling Correction Model Based on Dispersion and Coverage

1: Select m samples randomly from the data matrix $X_{N\times M}$.
2: For each sample X_{ij}, i is the number of VAP, j is the number of user, calculate the standard deviation σ_i and σ_j of all samples.

$$\sigma_i = \frac{\sum_{k}^{m} \left(i_k - \bar{i}\right)^2}{m},$$

$$\sigma_j = \frac{\sum_{j}^{m} \left(j_k - \bar{j}\right)^2}{m},$$

3: **if** $\sigma_i \geq tau_i \& \sigma_j \geq tau_j$ **then**
4: Samples with high discrete degree;
5: **else**
6: Samples with low discrete degree, must sample again.
7: **end if**
8: **if** $sum(AP_i) \neq 0 \& sum(STA_j) \neq 0$ **then**
9: All the rows and columns of the data matrix are covered by samples;
10: **else**
11: Some rows and columns of the data matrix are not covered by samples, must sample again.
12: **end if**
13: Obtain a valid sampling results, set for B.
14: According to the SVT matrix reconstruction algorithm, obtain the recovery data matrix $\hat{X}$.
15: Compare $X_{(N\times M)}$ with $\hat{X}_{(N\times M)}$, calculate the benchmark reconstruction error rate ε_0 as

$$\varepsilon_0 = \frac{\sum \left| X_{ij} - \hat{X}_{ij} \right|}{\sum \left| X_{ij} \right|}.$$

B. DETERMINE THE NUMBER OF DIRECT MEASUREMENTS

In the actual measurement, it is impossible to know the size of the result matrix rank before the measurement is performed. According to Eq.(4), how many direct measurements are sufficient to recover matrix accurately is difficult to determine. To discover the relationship between the sample number and the reconstruction performance, we change the sample and analyze the error-rate based on the real sensory data. Before we discuss the relationship, we give two definitions as follows.

Normalized Mean Absolute Error (NMAE) is a metric for measuring the reconstruction error after interpolation. That is, we calculate the error rate by comparing the recovered data with the raw data.

$$NMAE = \frac{\sum \left| X_{ij} - \hat{X}_{ij} \right|}{\sum \left| X_{ij} \right|}, \tag{10}$$

Sample Ratio (S-Ratio)

$$\mathrm{S-Ratio} = \frac{\mathrm{m}}{\mathrm{N \times M}}, \tag{11}$$

where m is a direct measurement of the sample size, $N * M$ is the total number of samples.

Based on above definitions, we characterize the relationship between NMAE and S-Ratio by increasing the sample number sequentially. Fig. 6 plots the results between them.

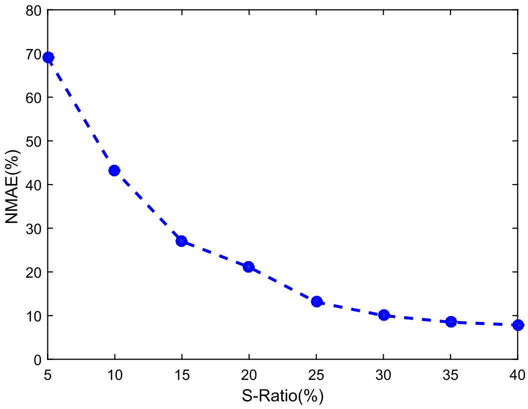


Fig. 6. **The relationship between NMAE and S-Ratio.**

We observe that when the sample number becomes large, the reconstruction error converges to a small value. Therefore, we have a conclusion that the monitoring matrix can be accurately recovered from the measurement matrix when the sample number is large enough, beyond which adding extra samples will not significantly increase the reconstruction accuracy.

Since the measurement results have those characteristics, so excessive number of samples is not helpful for matrix recovery. In order to minimize the number of direct measurements, we propose a sampling stopping condition for sequential sampling.

Considering that there are two matrices $A_{n\times m}$ and $B_{n\times m}$, we define $A \cong B$ if these two matrices satisfy the following expression:

$$\frac{\sqrt{\sum (A_{ij} - B_{ij})^2}}{\sqrt{\sum (\frac{1}{2}(A_{ij} + B_{ij}))^2}} \leq \varepsilon, \tag{12}$$

where ε is a small constant (0.03).

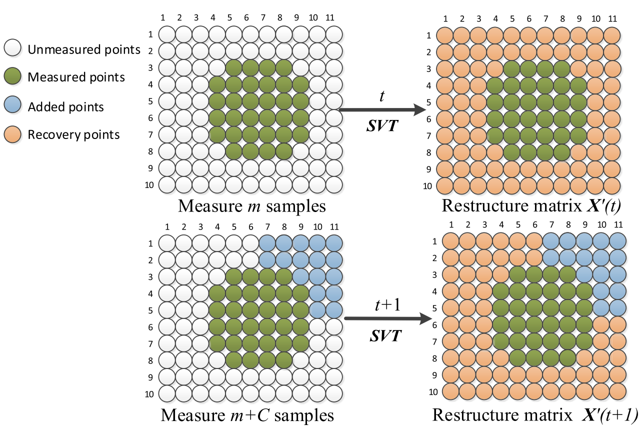


Fig. 7. **The process of the sampling stopping condition.**

This process is shown in Fig. 7. At the time of t, the m measurement node is randomly selected. At the time of $t + 1$, the number of measured nodes at t time was randomly added to the C measurement node. We obtain the recovered matrices denoted as $X'(t)$ and $X'(t+1)$, respectively. If these recovered matrices satisfy $X'(t) \cong X'(t + 1)$, then stop measurement. Otherwise, we will continue to randomly add C nodes until the conditions are met.

C. DETERMINE THE DIRECT MEASUREMENT SAMPLING SET

In order to provide a satisfactory accuracy and meet the real-time requirement, the direct measurement sampling set may change with time. Based on the above analysis, we propose the sampling stopping condition. However, which nodes should be chosen is a challenge.

When SVT algorithm is used to reconstruct the observation matrix, we find that the difference between the recovery value and the actual value of some nodes has a great influence on the NMAE reconstructed by the measurement matrix. We call this kind of node named "*KEY*" node. To quantitatively evaluate whether an entry is necessary, we measure the "*KEY*" value by computing the normalized difference values between adjacent time slots.

$$KEY(i,j) = \frac{\left|X'_{ij}(t+1) - X'_{ij}(t)\right|}{\frac{1}{2}\left|X'_{ij}(t+1) + X'_{ij}(t)\right|}. \tag{13}$$

This guides us to choose a appropriate measured point when the sample is not enough. Fig. 8 describes the adaptive sampling strategy. We calculate all the $KEY(i,j)$ in descending order at time $t + 1$, the former C corresponding to the corresponding subscript node to $t + 2$ time as a set of measurement nodes.

D. THE PROCESS OF MC-ASS

The complete MC-ASS scheme is shown in Algorithm 2. When the matrix is created in the time slot $t = 0$, pre-process strategy is performed to reduce the measured VAPs. In the training phase, due to the lack of enough history measurements to guide the sampling process, we construct the initial measurement matrix based on dispersion and coverage.

The process of adaptive sampling scheme is described from step 4 to step 13, and the while-do iteration will be ended when the similarity degree between matrix $X'(t)$ and $X'(t+1)$ is less than a threshold 0.03. At step 8, the sampling stopping condition is judged. If it achieves a reasonable recovery accuracy, and then jump out the endless cycle, otherwise, additional Ω entries which are determined by the "*KEY*" value should be participated in the next iteration.

According to detailed steps of MC-ASS algorithm, we can easily find the most of computing time is used for running two times SVT algorithm in step 4 and step 7, respectively, which is a popular and widely-used method for matrix completion problems [26]. In SVT algorithm, Lanczos iteration is used to compute singular values and the SVD should be computed in each iteration. Hence, its per-iteration complexity as low as mr time and $nr + m$ memory, where n represents the order of matrix and r represents the rank of matrix. Meanwhile, the algorithm converges sub-linearly in the worst-case and

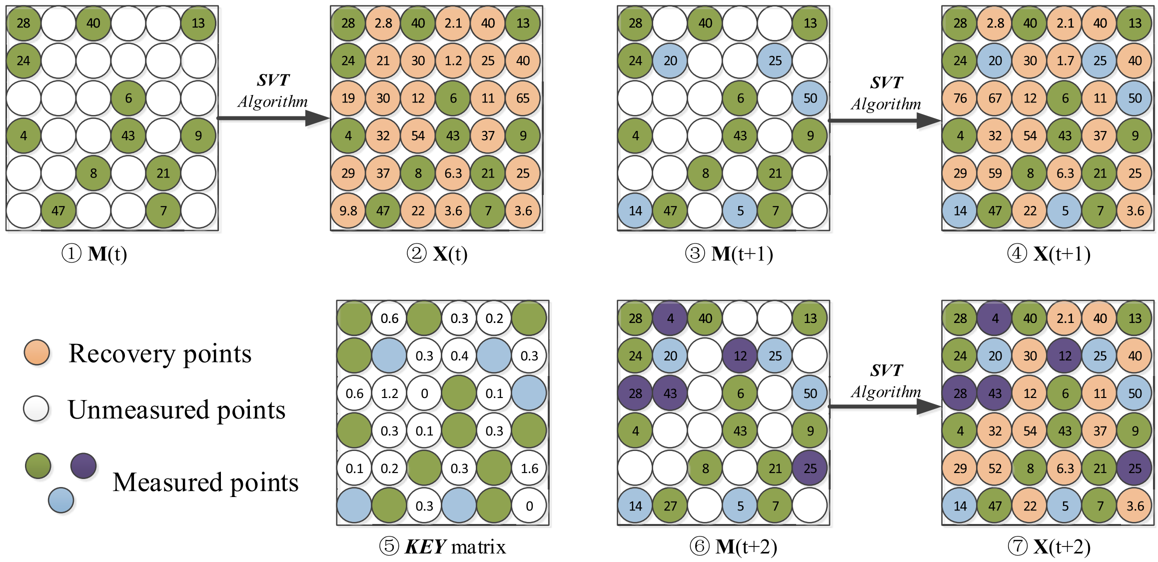


Fig. 8. **The adaptive sampling strategy.**

Algorithm 2 Matrix Completion-Adaptive Sequential Sampling (MC-ASS) Algorithm

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Input: the number of VAPs N, the number of STAs M;
Output: the recovery matrix X.

Initialize $t = 0$.
Initialize the number of direct measurement samples m, where $m < N \times M$ and $N \times M$ is the size of result matrix.
Obtain the sampling matrix $B(t)$ through the Sampling correction model based on dispersion and coverage.
Obtain the direct measurement matrix $M(t)$ according to $B(t)$. Run the SVT algorithm to reconstruct $M(t)$ and get recovery matrix $X'(t)$.
$t = t + 1$, add Ω points to get $B(t + 1)$ on the basis of m, where $\Omega = 0.5alogb$, $a = max(N, M)$, $b = min(N, M)$ and $m \cap \Omega = \emptyset$.
Obtain the direct measurement matrix $M(t+1)$ according to $B(t + 1)$.
Run the SVT algorithm to reconstruct $M(t + 1)$ and get recovery matrix $X'(t + 1)$.
if $X'(t) \cong X'(t+1)$ **then**
    $X'(t + 1)$ is the result matrix;
else
    Calculate the value of KEY by $(i, j) \notin (m \cup \Omega)$, and descending order. Then choose Ω points which correspond to the former Ω KEY value.
end if
Obtain the result matrix X'.

---

requires $O(1/\varepsilon)$ iterations, where ε is the convergence accuracy which always be a sufficiently small value like 10^{-4}. From the above, the total time complexity of our MC-ASS algorithm is close to $O(mr/\varepsilon)$.

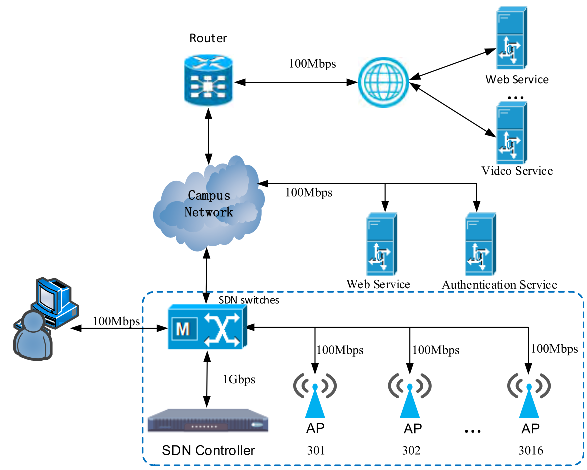


Fig. 9. **Experimental platform hardware device configuration information.**

VI. EVALUATION

In this section, the prototypical MC-ASS implementations in real network, and accuracy and error-rates are evaluated.

A. EXPERIMENT SETUP

The practical deployment of the experimental platform in an experimental building is under the way, and the plane distribution is shown in Fig. 9. Fig. 10 shows the picture of this lab. There are a number of IEEE 802.11n enabled APs running distributed in each office room across this floor, SDN switches and SDN Controller. TABLE 1 shows the detailed configuration.

B. EXPERIMENT RESULTS

There are two purposes of the experimental tests: one is to verify the accuracy of the signal strength, associated user number and data flow of a individual VAP node. The other is to verify the low measurement sample rate and high accuracy

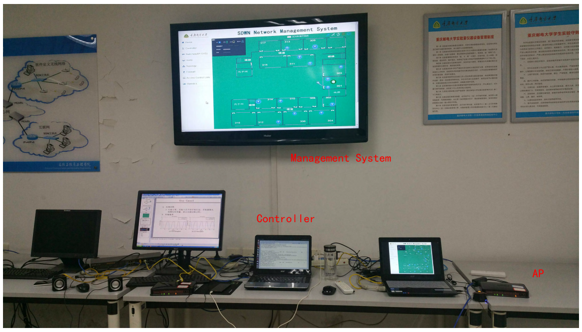


Fig. 10. Experimental platform hardware device configuration information.

TABLE 1. Experimental platform hardware device configuration information.

Device	Configuration Information	Number
IBM Server	System: CentOS6.3; CPU: E5300 2.60GHz; Memory: 3GB;	1
OpenFlow Switch	BiWei S6228SP; 24 port	1
Netgear WNDR3800 (Wireless Access Point)	Kernel: 3.10; CPU: Atheros AR7161 rev 2 680MHz; RAM: 128M; Flash: 16M	15

recovery effect of the whole network performance measurement method.

1) COMPARISON OF SAMPLING METHODS FOR INITIAL WINDOW

To investigate the performance of the proposed correction model, we compare it to the Bernoulli model and the Uniform model. In this experiment, with the AP data traffic rate as experimental data, the improved model will make comparison with Bernoulli model and uniform sampling model so as to acquire m points in three ways from the initial matrix in accordance with the sampling rate of 28.6%. The number of VN nodes N is equal to 90 in this experiment, sliding window size T equals 240, and a total number of sampling calculations M equals 30. The results are shown in Fig. 11.

$$\varepsilon_0 = \frac{\sum \varepsilon}{M}, \qquad \tau = \frac{\sum |\varepsilon - \varepsilon_0|}{M}. \tag{14}$$

Through the above three methods of the comparative analysis, we can see that the proposed scheme has better performance.

2) THE RESULT OF SINGLE VAP PERFORMANCE

In order to verify the accuracy of the measurement method, in the previous built SDWN experimental bed, the Fluke AirCheck Wi-Fi Tester is placed aside the AP which is about to be measured so as to detect and record the related performance data of AP in real-time. To run the Wi-Fi tester and meanwhile implement the collection of data with the VAP-SUT measurement method, to compare the recorded measurement results between the controller and Wi-Fi tester. We carry out a quantitative analysis about the error rate between the VAP-SUT measured value and the true value.

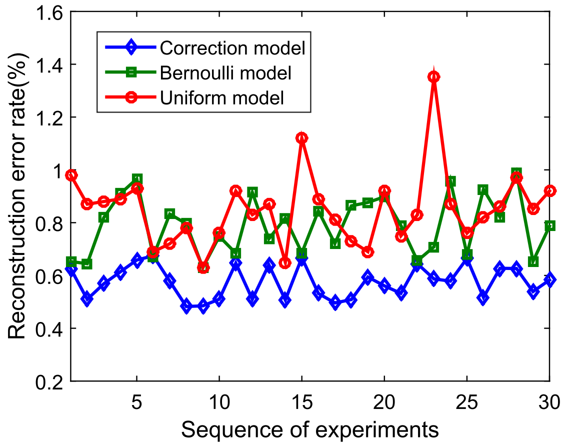


Fig. 11. Comparison of sampling models.

In the measurement process, in order to avoid the lack of a comparison between the Wi-Fi tester and the proposed method of VAP-SUT measurement method due to the different time of the implementation of a single measurement, this section takes the test results made during the period from 9:00am to 7:00pm, making the measurement data of half an hour as a group, 20 groups relatively for three data, and thus making the median of each test data as valid data.

Fig. 12 shows the results of the 20 groups of measurement results for the Wi-Fi tester and the VAP-SUT measurement method. The abscissa indicates the serial number of each group and the ordinate indicates the VAP signal strength, VAP associated user number and VAP data flow.

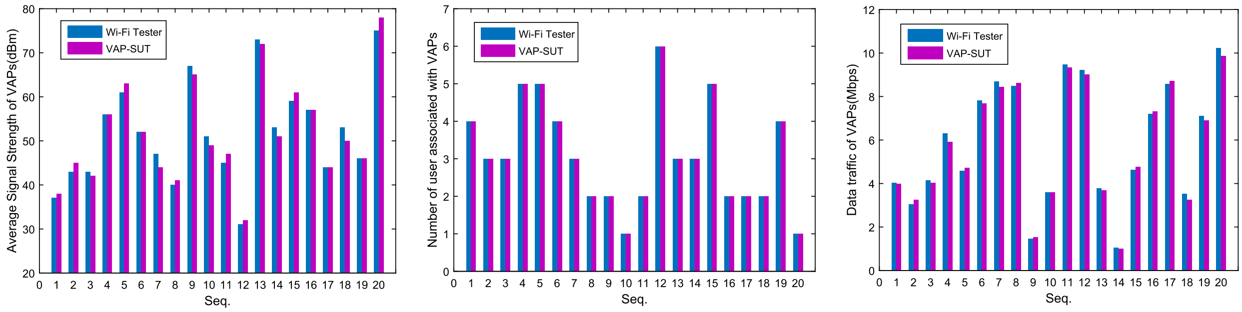
According to the measurement results of Fig. 12, based on the standard with the test results of the Wi-Fi tester, the normal mean absolute error (NMAE) of (a), (b) and (c) are respectively calculated by the measurement result of the Wi-Fi tester as shown in TABLE 2. Obviously, the measurement results are close to the measurement results of the Wi-Fi tester at a probability of at least 98%, and the accuracy of the number of VAP associated users is 100%.

TABLE 2. The result of NMAE.

	The AP signal strength	The number of associated users	Data flow
NMAE	1.27%	0%	1.84

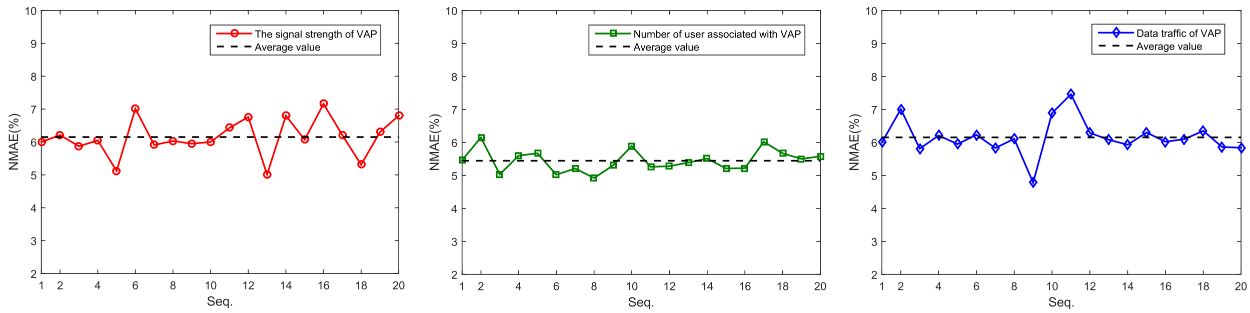
3) VERIFY THE ACCURACY OF THE VAP PERFORMANCE MEASUREMENT METHOD FOR THE ENTIRE NETWORK

In order to verify the accuracy and low sample rate of the VAP performance measurement method based on the MC-ASS algorithm, in the previous built SDWN experimental bed, the controller collect all the signal strength, associated user number and data flow rate of 90 VAP nodes as a reference data set, while running on VAP performance measurement system based on the MC-ASS algorithm. Then to make the comparison of the performance data when the MC-ASS algorithm is executed and all the collected data set, and the NMAE value and the S-Ratio value are obtained.



(a) (b) (c)

Fig. 12. **Compare the WiFi-Tester and VAP-SUT. (a) AP signal strength. (b) Number of associated users. (c) Data flow.**



(a) (b) (c)

Fig. 13. **The NMAE of the three performance data. (a) AP signal strength. (b) Number of associated users. (c) Data flow.**

Same as in the previous experiment, this section takes the test results during the measurement time from 9:00am to 7:00pm, making half an hour of measurement data as a group, 20 groups relatively for three data, and thus making the median of each test data as valid data. Based on the reference data set of the whole VAPs which is collected by the VAP-SUT measurement method, and thus calculating the error NMAE and the sample rate S-Ratio after each data is recovered by the MC-ASS algorithm.

In Fig. 13, the abscissa indicates the serial number of each group, and the ordinate represents the calculated NMAE error, where the dotted line represents the average of the NMAE error. It can be seen that the the NMAE error of three performance indicators of SUT in the VAP performance measurement system is relatively stable, where the NMAE of the VAP signal strength basically is controlled at 6.0%, the NMAE of the VAP associated with the number of users basically is controlled at 5.5%, and the NMAE of the VAP data traffic NMAE basically is controlled at 6.2.

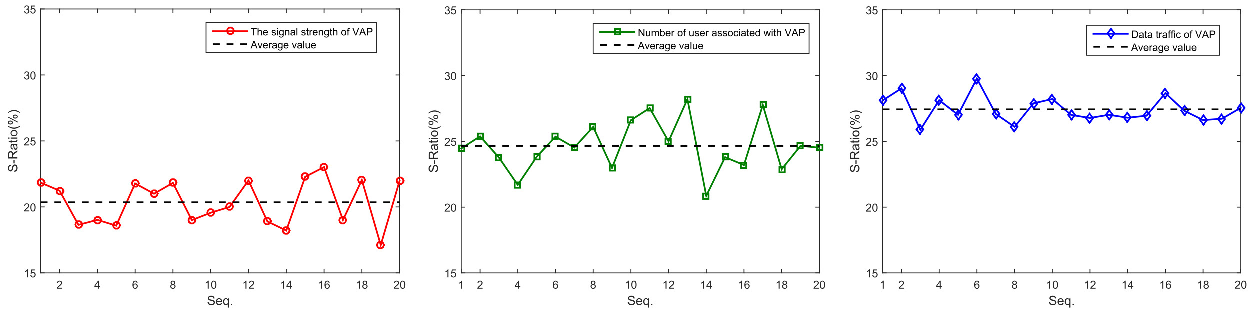
In order to verify the low sample rate characteristics of the MC-ASS algorithm, Fig. 14 shows the S-Ratio of the three performance indicators of the MC-ASS algorithm, where the dashed lines represent the average. The abscissa indicates the serial number of each group, and the ordinate indicates the measured sample rate. It can be seen that the S-Ratio of VAP signal strength is controlled at 20%, the S-Ratio of VAP associated users is controlled at 25%, and the S-Ratio of VAP data is basically controlled at 27%.

C. SYSTEM PERFORMANCE

Fig. 15 shows the data traffic of the central switching node over time in the experimental platform. APs in the system exchange data with the controller and Internet through the node. In process of the test, a data stream of 10 Mbps was applied to each VN as the background traffic of the experiment. By taking the whole network method and MC-ASS scheme to measure the network performance of VN in the same test environment, and comparing the results of the two methods, it can be seen that the consumption of the whole network measurement is 3 times of the MC-ASS measurement mode. The simulation results show that our scheme can achieve highly accurate recovery performance with less resource consumption.

D. DISCUSSION ABOUT THE SCHEME

The above architecture combines the benefits of MC and SDN which only requires modification at AP side. The results indicate that the performance measurement method for VAP can realize VAP performance measurement of the entire network and significantly reduce the measurement sample rate and error while ensuring stability. Based on the research on VAP performance measurement method, it can reduce AP's load and save the storage resources. What's more, the



(a) (b) (c)

Fig. 14. **The S-Ratio of the three performance data. (a) AP signal strength. (b) Number of associated users. (c) Data flow.**

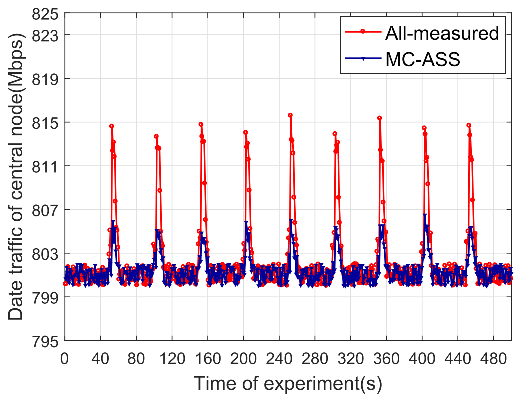


Fig. 15. **Comparison of the center node data traffic.**

measurement data can facilitate the research on load balancing, handover, energy saving and other network optimization works.

VII. CONCLUSION

As the main challenge for WNV management, the perception of the complete virtual network status in real-time is very difficult under insufficient resources. In this paper, motivated by the emerging MC theory, we exploit an intelligent network measurement framework based on the MC techniques to monitor and analyze real-time network performance, which can recover incomplete matrix with partial network measurements. We have formulated a mathematical model which can determine the smallest sample sizes that makes matrix reconstruction reach a certain accuracy level. Furthermore, a dynamic adjustment strategy is designed to continuously amend the direct measurement VAP. For practical implementation, MC-ASS offers the invaluable quality monitoring for Controller's management which can reduce the network overhead obviously.

There are three avenues for our future work. Firstly, exploit the correlations between multiple environmental factors to further improve the accuracy of estimation, such as radio interference, temperature and etc. Secondly, study the tradeoff between the computation time and accuracy in environment reconstruction. Thirdly, it is also interesting and challenging that the measurement results be transmitted efficiently to the Controller.

We will also extend the system to be able to measure other type performances, such as, traffic, delay, etc. Our system leverages the benefit of SDN property, and thereby it can be easily applied to the future 5G communication system. Furthermore, the idea of design in this paper could also be enlightening.

REFERENCES

[1] L. Suresh, J. Schulz-Zander, R. Merz, A. Feldmann, and T. Vazao, "Towards programmable enterprise WLANS with Odin," in *Proc. Workshop Hot Topics Softw. Defined Netw.*, 2012, pp. 115–120.

[2] C. Xu, W. Jin, G. Zhao, H. Tianfield, S. Yu, and Y. Qu, "A novel multipath-transmission supported software defined wireless network architecture," *IEEE Access*, vol. 5, pp. 2111–2125, 2017.

[3] I. F. Akyildiz, S. Nie, S.-C. Lin, and M. Chandrasekaran, "5G roadmap: 10 key enabling technologies," *Comput. Netw.*, vol. 106, pp. 17–48, Sep. 2016.

[4] Z. Shu *et al.*, "Traffic engineering in software-defined networking: Measurement and management," *IEEE Access*, vol. 4, pp. 3246–3256, 2016.

[5] K. Yu, T. Ito, and T. Hara, "A measurement study on virtualization overhead for applications of industrial automation systems," in *Proc. IEEE Int. Conf. Emerg. Technol. Factory Autom.*, Sep. 2016, pp. 1–8.

[6] X. Wang, C. Xu, G. Zhao, and S. Yu, "Tuna: An efficient and practical scheme for wireless access point in 5G networks virtualization," *IEEE Commun. Lett.*, to be published.

[7] M. T. Nguyen and K. A. Teague, "Compressive sensing based data gathering in clustered wireless sensor networks," in *Proc. IEEE Int. Conf. Distrib. Comput. Sensor Syst.*, May 2014, pp. 187–192.

[8] J. Xiong, J. Zhao, and L. Chen, "Efficient data gathering in wireless sensor networks based on matrix completion and compressive sensing," *Int. J. Online Eng.*, vol. 9, no. S7, pp. 61–64, 2013.

[9] M. Malboubi, Y. Gong, W. Xiong, C.-N. Chuah, and P. Sharma, "Software defined network inference with passive/active evolutionary-optimal probing (sniper)," in *Proc. Int. Conf. Comput. Commun. Netw.*, 2015, pp. 1–8.

[10] K. Xie, L. Wang, X. Wang, J. Wen, and G. Xie, "Learning from the past: Intelligent on-line weather monitoring based on matrix completion," in *Proc. IEEE Int. Conf. Distrib. Comput. Syst.*, Jun. 2014, pp. 176–185.

[11] K. Xie *et al.*, "Recover corrupted data in sensor networks: A matrix completion solution," *IEEE Trans. Mobile Comput.*, vol. 16, no. 5, pp. 1434–1448, May 2017.

[12] A. Yassine, H. Rahimi, and S. Shirmohammadi, "Software defined network traffic measurement: Current trends and challenges," *IEEE Instrum. Meas. Mag.*, vol. 18, no. 2, pp. 42–50, Apr. 2015.

[13] M. Malboubi, L. Wang, C. N. Chuah, and P. Sharma, "Intelligent SDN based traffic (de)Aggregation and Measurement Paradigm (iSTAMP)," in *Proc. IEEE Conf. Comput. Commun. (INFOCOM)*, Apr. 2014, pp. 934–942.

[14] Y. Gong, X. Wang, M. Malboubi, S. Wang, S. Xu, and C.-N. Chuah, "Towards accurate online traffic matrix estimation in software-defined networks," in *Proc. ACM SIGCOMM Symp. Softw. Defined Netw. Res.*, 2015, p. 26.

[15] A. Tootoonchian, M. Ghobadi, and Y. Ganjali, "OpenTM: Traffic matrix estimator for openflow networks," in *Passive and Active Measurement*, vol. 6032. 2010, pp. 201–210.
[16] C. Liu, A. Malboubi, and C.-N. Chuah, "OpenMeasure: Adaptive flow measurement & inference with online learning in SDN," in *Proc. Comput. Commun. Workshops*, 2016, pp. 47–52.
[17] C. Cao, L. Luo, Y. Gao, W. Dong, and C. Chen, "TinySDM: Software defined measurement in wireless sensor networks," in *Proc. Int. Conf. Inf. Process. Sensor Netw.*, 2016, p. 18.
[18] Z. Qin, Y. Liu, Y. Gao, M. Elkashlan, and A. Nallanathan, "Wireless powered cognitive radio networks with compressive sensing and matrix completion," *IEEE Trans. Commun.*, vol. 65, no. 4, pp. 1464–1476, Apr. 2017.
[19] J. Wang, S. Tang, B. Yin, and X.-Y. Li, "Data gathering in wireless sensor networks through intelligent compressive sensing," in *Proc. IEEE INFOCOM*, Mar. 2012, pp. 603–611.
[20] H. Zheng, F. Yang, X. Tian, X. Gan, X. Wang, and S. Xiao, "Data gathering with compressive sensing in wireless sensor networks: A random walk based approach," *IEEE Trans. Parallel Distrib. Syst.*, vol. 26, no. 1, pp. 35–44, Jan. 2015.
[21] J. Cheng, Q. Ye, H. Jiang, D. Wang, and C. Wang, "STCDG: An efficient data gathering algorithm based on matrix completion for wireless sensor networks," *IEEE Trans. Wireless Commun.*, vol. 12, no. 2, pp. 850–861, Feb. 2013.
[22] K. Xie *et al.*, "Sequential and adaptive sampling for matrix completion in network monitoring systems," in *Proc. IEEE Conf. Comput. Commun.*, Apr. 2015, pp. 2443–2451.
[23] M. Polverini, A. Iacovazzi, A. Cianfrani, A. Baiocchi, and M. Listanti, "Traffic matrix estimation enhanced by SDNs nodes in real network topology," in *Proc. IEEE INFOCOM*, Apr. 2015, pp. 300–305.
[24] C. Boutsidis, M. W. Mahoney, and P. Drineas, "An improved approximation algorithm for the column subset selection problem," *J. Post Keynesian Econ.*, vol. 10, no. 4, pp. 509–611, 2008.
[25] B. Recht, M. Fazel, and P. A. Parrilo, "Guaranteed minimum-rank solutions of linear matrix equations via nuclear norm minimization," *SIAM Rev.*, vol. 52, no. 3, pp. 471–501, 2010.
[26] J.-F. Cai, E. J. Candes, and Z. Shen, "A singular value thresholding algorithm for matrix completion," *SIAM J. Optim.*, vol. 20, no. 4, pp. 1956–1982, 2010.
[27] W. Kellerer, A. Basta, and A. Blenk, "Using a flexibility measure for network design space analysis of SDN and NFV," in *Proc. IEEE Conf. Comput. Commun. Workshops (INFOCOM)*, Apr. 2016, pp. 423–428.
[28] T. Huang, S. Yan, F. Yang, T. Pan, and J. Liu, "Building SDN-based agricultural vehicular sensor networks based on extended Open vSwitch," *Sensors*, vol. 16, no. 1, p. 108, 2016.
[29] T. Tanaka, K. Abe, S. Aust, T. Ito, H. Yomo, and S. Sakata, "Automatic and cooperative sleep control strategies for power-saving in radio-on-demand WLANs," in *Proc. Green Technol. Conf.*, 2013, pp. 293–300.
[30] Z. Liu, Y. Liu, Z. Gong, and L. Chen, "A mutil-rate access point selection policy in IEEE 802.11 WLANs," in *Proc. Int. Conf. Multimedia Technol.*, Jul. 2011, pp. 63–67.
[31] Y. Mo, Y. Cai, and B. Wang, "A novel indoor localization method based on virtual AP estimation," in *Proc. IEEE Int. Conf. Commun.*, Jun. 2012, pp. 5508–5512.
[32] L. Kong *et al.*, "Data loss and reconstruction in wireless sensor networks," *IEEE Trans. Parallel Distrib. Syst.*, vol. 25, no. 11, pp. 2818–2828, Nov. 2014.
[33] E. J. Candès and T. Tao, "The power of convex relaxation: Near-optimal matrix completion," *IEEE Trans. Inf. Theory*, vol. 56, no. 5, pp. 2053–2080, May 2010.

XINHENG WANG is currently pursuing the Ph.D. degree with the Future Networks Research Institute, Chongqing University of Posts and Telecommunications, China. His research interests include software-defined wireless network, NFV, and network measurement.

CHUAN XU received the Ph.D. degree in control theory and engineering from Chongqing University, China, in 2012. He is currently an Associate Professor with the Chongqing University of Posts and Telecommunications, China. He has been involved in several Chinese Government Projects, including 973 projects and NSFC projects. He has published over 30 articles in internationally major journals and conferences and holds several granted patents. His research interests include analysis in mobile networks, software-defined wireless networking, and network management.

GUOFENG ZHAO is currently a Full Professor with the School of Communication and Information Engineering, Chongqing University of Posts and Telecommunications. He has involved in a number of national and international projects. His main research interests include software-defined networking, network management, and the modeling of wired and wireless networks. He is serving as a TPC member for international conferences and journals.

KUN XIE received the B.S. degree in communication engineering, and the M.S. and Ph.D. degrees in computer application from Hunan University, Changsha, China, in 2001, 2004, and 2007, respectively. She was a Post-Doctoral Fellow with the Department of Computing, The Hong Kong Polytechnic University, from 2007 to 2010. She was a Visiting Researcher with the Department of Electrical and Computer Engineering, State University of New York at Stony Brook, from 2012 to 2013. She is currently an Associate Professor with Hunan University. She has published over 60 papers in major journals and conference proceedings, including top journals IEEE/ACM TON, IEEE TWC, IEEE TC, JPDC, and JCST, and top conferences INFOCOM, ICDCS, and IWQoS. Her research interests include wireless network and mobile computing, network management and control, cloud computing and mobile cloud, and big data.

SHUI YU (SM'12) is currently a Senior Lecturer with the School of Information Technology, Deakin University. He has authored two monographs and edited two books, over150 technical papers, including top journals and top conferences, such as IEEE TPDS, IEEE TC, IEEE TIFS, IEEE TMC, IEEE TKDE, IEEE TETC, and IEEE INFOCOM. He initiated the research field of networking for big data in 2013. His research interest includes security and privacy in networking, big data, and cyberspace, and mathematical modeling. He is a member of the Deakin University Academic Board 2015–2016, AAAS, and ACM, the Vice Chair of the Technical Subcommittee on Big Data Processing, Analytics, and Networking of the IEEE Communication Society, and a member of the IEEE Big Data Standardization Committee. His h-index is 21.

Dr. Yu actively serves his research communities in various roles. He has served over 50 international conferences as a member of the organizing committee, such as a Publication Chair for the IEEE Globecom 2015 and the IEEE INFOCOM 2016, and a TPC Co-Chair for the IEEE BigDataService 2015 and the IEEE ATNAC 2014 and 2015. He is currently serving on the Editorial Boards of the IEEE Communications Surveys and Tutorials, the IEEE Access, the IEEE Internet of Things Journal, and a number of other international journals.