The Prediction Analysis of Cellular Radio Access Network Traffic: From Entropy Theory to Networking Practice

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ABSTRACT

Although the research on traffic prediction is an established field, most existing works have been carried out on traditional wired broadband networks and rarely shed light on cellular radio access networks (CRANs). However, with the explosively growing demand for radio access, there is an urgent need to design a traffic-aware energy-efficient network architecture. In order to realize such a design, it becomes increasingly important to model the traffic predictability theoretically and discuss the traffic-aware networking practice technically. In light of that perspective, we first exploit entropy theory to analyze the traffic predictability in CRANs and demonstrate the practical prediction performance with the state-of-the-art methods. We then propose a blueprint for a traffic-based software-defined cellular radio access network (SDCRAN) architecture and address the potential applications of predicted traffic knowledge into this envisioned architecture.

INTRODUCTION

Traffic modeling and prediction are at the heart of the evaluation of the performance of telecommunications networks and attract much attention [1–3]. Yet, conventional research of traffic prediction, although an established field, has been mostly concentrated on traditional wired broadband networks [2] and rarely sheds light on cellular radio access networks (CRANs). But the situation needs to be changed as the popularity of mobile devices (e.g. iPhone) and applications (e.g. Facebook) on them makes the traffic in CRANs shift from being voice-centric to data-centric [4]. Meanwhile, the rebuilding of a traffic-aware energy-efficient architecture for cellular networks is becoming a trend [4–6]. However, since CRANs have more stringent constraints on radio resources [7], relatively expensive billing polices and different user behaviors due to mobility [8] and thus exhibit distinct traffic characteristics, research results from wired broadband network traffic cannot be directly applied to CRANs. Therefore, motivated by incorporating traffic variations into the future cellular network design [4], this article attempts to study and predict the traffic dynamics in CRANs and provide certain guidance over how to apply the predicted traffic to the design of future CRAN architecture.

Recently, tools from information theory [9] have been introduced in various prediction scenarios such as atmosphere or climate and given a considerable number of intuitive conclusions [10, 11]. The basic idea is that *entropy* offers a precise definition of the informational content of predictions by the corresponding probability distribution functions (PDFs), and it possesses good generality because it makes minimal assumption on the model of the studied scenario. The entropy approach is therefore suitable for gauging the traffic predictability based on certain prior information from history or from neighboring cells. In this article, with the help of real traffic records of roughly 7000 base stations (BSs) in one month from China Mobile, we use entropy theory to understand the contributions of temporal and spatial dimensions and the inter-service relationship to traffic prediction in CRANs and provide some conclusions. Further, we describe some practical prediction means and present the relevant performance.

After validating the traffic predictability, this article proceeds to address the practical applications of the predicted traffic. Nowadays, as the core network architecture is evolving toward software-defined networks (SDNs) [12], the predicted traffic could significantly contribute to network management in this future architecture. In SDNs, a control plane, which makes traffic routing decisions, is separated from the underlying data plane, which takes charge of traffic forwarding. Meanwhile, SDNs provide various open application interfaces (APIs) to external application engines (e.g. access control), and thus facilitate network programmability. As a result, the configuration process in SDNs can become more flexible and scalable. Besides, traffic knowledge can be exploited in an easier manner, so as to optimize routing policies and avoid congested routers. Inspired by this principle and methodology of traffic-aware SDNs, we later provide a

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blueprint for a traffic-based software-defined CRAN (SDCRAN) architecture and primarily focus on the potential applications of traffic prediction in this architecture from different scales.

Traffic Prediction: Theoretical Analysis and Practical Performance

Prediction Dataset Description and Analysis Methodology

In order to smoothly perform prediction analysis, this article collects the anonymous traffic records of nine mobile switching centers (MSCs) and serving GPRS switching nodes (SGSNs) with 7000 BSs. The collected dataset includes all the calls, short message service (SMS), and data logs in both rural and urban areas of around 780 km^2, serving about three million subscribers. The duration of the dataset spans from March 2012 to April 2012. The dataset also contains the fields such as timestamp and cell ID to record when and where one call/SMS/session appears. For the services of voice and data, call duration and transmitted volume are also incorporated in each record.

After obtaining the massive dataset, a preprocessing procedure is conducted to sort the traffic records by time and cell ID in the first place, and then compute voice, text, and data traffic according to the number of voice (e.g. calls), the count of texts (e.g. SMSs) and the volume of transmitted data during a certain period (e.g. 30 minutes) within the same cell, respectively. To ease the following analysis, the traffic during a certain period i within a cell is quantized into Q levels, based on[1]

$$\text{QuantizedTraffic}(i) = \left\lfloor Q \cdot \frac{\text{RealTraffic(i)-MinimumTraffic}}{\text{MaximumTraffic-MinimumTraffic}} \right\rfloor$$

Thus, with the quantized traffic values of every period within each cell, the corresponding traffic distributions can be obtained. For example, Fig. 1 (Right) depicts the PDF in one cell with respect to the quantitized traffic and shows that both voice and text traffic are medium while data traffic is lower.

The entropy, which Shannon utilizes to measure the uncertainty of events [9], is defined by a discrete random variable X with possible values $\{x_1, \dots, x_n\}$ and the corresponding PDF $P(X)$:

$$H(X) = -\sum_{i=1}^{n} p(x_i) \log_b p(x_i), \tag{1}$$

where b is the base of the logarithm and commonly takes the value of 2, when the unit of entropy is 1 bit. According to this definition of entropy, traffic distributions, which heavily depend on the specific location characteristics (e.g. residential or central business districts, etc.) and the related user behaviors, lead to distinct entropy values. Therefore, it is possible to use entropy to describe the uncertainty of traffic in CRANs. For example, Fig. 1 (Left) depicts the traffic variations of two typical cells in one week. For the cell with the blue dash line, the entropies for voice, text, and data traffic are 2.1834, 2.1733, and 1.5472, respectively. In contrast, the other cell with the red solid line has a comparatively larger data traffic entropy of 2.0415, which implies a more volatile traffic variation in this cell.

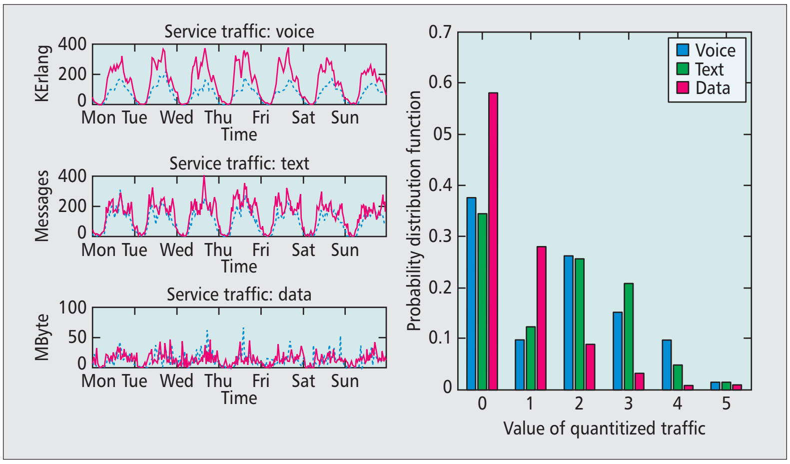

Figure 1. (Left) Two typical cells' traffic in one week with different entropies. The random entropies of voice, text and data for the cell in the red solid line are 2.4034, 2.1177, and 2.0415 while the counterparts for the cell in the blue dash line are 2.1834, 2.1733, and 1.5472. (Right) The corresponding probablity distribution function with respect to the traffic in the cell in the blue dash line on the left side.

Meanwhile, the traffic variations illustrated in Fig. 1 (Left) imply that the traffic of the voice service varies more dramatically than that of the others. Indeed, this phenomenon applies to other cells. Fig. 2 plots the cumulative distribution functions (CDFs) with respect to the traffic entropies in the cells. Besides, Table 1 lists a brief summarization of the entropy calculation results. Both of them express that, among all the services, voice traffic has the largest entropy, with mean of 2.1429 and minimum of 1.0936, and thus its traffic distribution is more uniform. Comparatively, data traffic is relatively stable since the entropy of data traffic is the smallest and it is lower than 1 bit for more than 70 percent of cells.

Similarly, traffic predictability can be examined from different perspectives if we depend on the following different prior information cases and calculate the conditional entropies:

- Temporal conditional entropy of traffic based on a certain preceding duration.
- Spatial conditional entropy of traffic based on adjacent cells.
- A specific service's conditional entropy based on traffic of other services.

Prediction Analysis: To What Extent Is the Prior Information Required?

Traffic prediction relies on the periodical similarity of the traffic itself and requires a certain quantity of prior information to reduce uncertainty. Generally speaking, as the amount of prior information increases, prediction performance will be improved. In other words, the residual uncertainty decreases along with the

[1] The MaximumTraffic and MinimumTraffic are the maximal and minimal traffic values of the cell in the timespan of interest. It should be noted here that the quantization error will affect the calculation accuracy of random entropy at some extent, but it would be reduced when we later calculate the conditional entropy using the operation of subtraction.

increase in aggregated prior information. Yet, this rationale needs further theoretical investigations. Recall that in [9] the conditional entropy of two random variables X and Y, which take possible values $\{x_1, \dots, x_n\}$ and $\{y_1, \dots, y_n\}$ with the joint PDF $P(X, Y)$, is defined as

$$H(X|Y) = \sum_{i,j} p(x_i, y_j) \log \frac{p(y_j)}{p(x_i, y_j)} = H(X,Y) - H(Y) \quad (2)$$

Therefore, as Eq. 2 implies, how to characterize and measure the residual uncertainty exactly falls into the scope of conditional entropy.

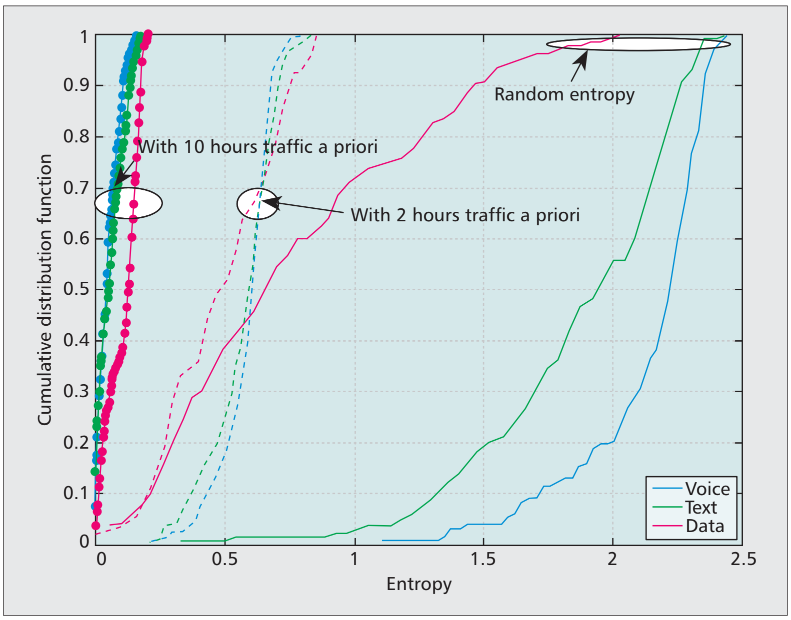

Figure 2. The cumulative density functions with respect to the corresponding entropies of traffic under the cases: no prior information, two hours' and ten hours' information.

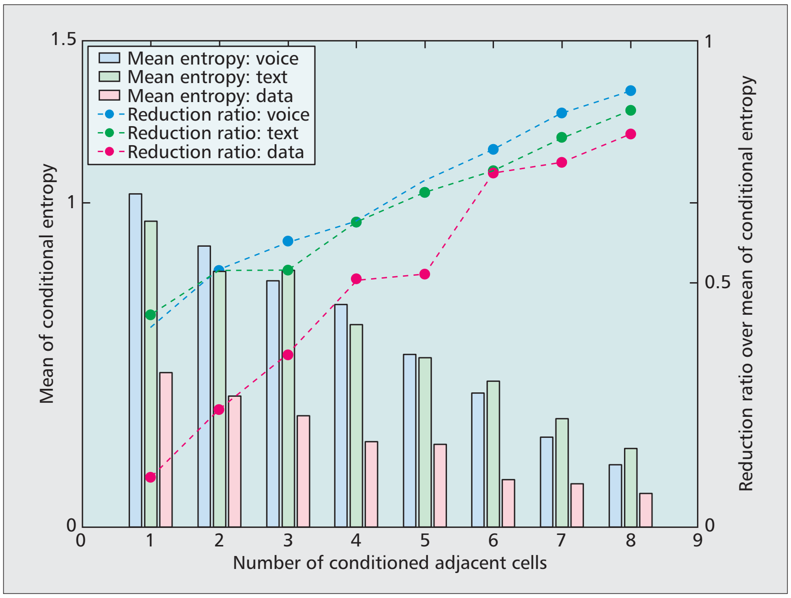

Figure 3. The mean of conditional entropies versus the number of conditioned adjacent cells.

Temporal Dimension — Researchers have demonstrated the feasibility of predicting traffic in broadband networks based on its self-similarity or periodicity [2]. However, these previous discussions merely focused on a single service type in the core networks. For CRANs, it is necessary to extend the discussions to all types of services (i.e. voice, text, and data). This section aims to answer the question of how long a period of historical traffic is required for a confident prediction of future traffic? In other words, what is the minimum temporal information for a given conditional entropy constraint?

Figure 2 plots the CDFs of the conditional entropies in the cells with the previous two and 10 hours of traffic information. As it demonstrates, by introducing preceding traffic information, uncertainty can be reduced effectively. Moreover, with equal preceding hours of traffic information, the conditional entropies of voice traffic decrease most rapidly, even though the random entropy of voice is comparatively larger. For example, voice's temporal conditional entropy with two hours of historical information decreases from 2.1429 bit to 0.5880 bit on average, which indicates that it would become much easier to trace the variation of voice traffic, given two hours of temporal information. Table 1 further states that when the historical time increases to 12 hours, voice's conditional entropy shrinks to less than 0.1 bit, a reduction of over 80 percent compared to the case without any prior information. As a result, the more historical traffic information is provided, the more precisely and easily the quantized traffic can be predicted. Additionally, compared to voice and text services, the temporal conditional entropy of data traffic degrades slowest when the information of the preceding hours is adopted. Therefore, it is more challenging to predict data traffic based on historical traffic knowledge.

Spatial Dimension — To guarantee a full coverage over the region of interest and ensure quality of experience all the time, mobile operators deploy coverage-overlapped adjacent cells, which in turn lead to some similarities between traffic in the adjacent cells. Meanwhile, user mobility behavior adds to the spatial relevancy in the traffic. In this section we attempt to measure this spatial relevancy and describe how much information adjacent cells could provide.

Figure 3 demonstrates how the mean of spatial conditional entropy varies with the number of considered adjacent cells. As Fig. 3 illustrates, the traffic knowledge from adjacent cells can enhance predictability. For example, by Table 1 the mean of spatial conditional entropy with voice traffic information from three adjacent cells reduces to 0.9043 bit. As the number of adjacent cells exploited for traffic information rises, the mean of spatial conditional entropy continues to decline. On the other hand, slightly less than the contribution of temporal relevancy to traffic prediction, the spatial factor decreases the entropy mean to 30 percent, depending on the traffic information from six adjacent cells. Similar to the effect of temporal information,

Fig. 3 implies that the relevant spatial information exhibits a larger contribution to the predictability of voice and text traffic than that of data traffic.

Inter-Service Relationship — As mentioned above, traffic of the three typical service types (i.e. voice, text and data) is influenced by several common factors, such as idle/busy time of a person. Hence, it seems viable to enhance the traffic predictability of one service type by regarding another as prior information. In the following, we try to discuss how much positive impact the traffic of one service type has on predicting that of another service?

Because of space limitations, we provide the important entropy values in Table 1 and omit the corresponding CDFs. As indicated in Table 1, the traffic of text contributes a lot to the prediction of voice traffic, taking into account the 0.7463 bit decrease in the calculated entropy. However, the contribution of data to the prediction of voice is negligible as it merely leads to a reduction of 0.1361 bit. Meanwhile, Table 1 also indicates that owing to the unique burst characteristics of data traffic, the effect of voice and text on data traffic prediction is relatively smaller. Thus, it is reasonable to reach the conclusion that the inter-service relevancy between data and voice/text is limited but that between voice and text could be further exploited to obtain higher prediction accuracy.

Service	Calculation conditioned on	Entropy			
		Mean	Variance	Min	Max
Voice	None	2.1429	0.0680	1.0936	2.4539
	2 preceding hours	0.5880	0.0107	0.2051	0.7982
	12 preceding hours	0.0228	0.0013	0	0.1399
	3 Adjacent cells	0.9043	0.0581	0.4517	1.7000
	Text	1.3966	0.0851	0.5794	1.9836
	Data	2.0068	0.0730	1.0841	2.4142
	Text and data	1.2956	0.0920	0.5030	1.9339
Text	None	1.8796	0.1552	0.3053	2.4572
	12 preceding hours	0.0353	0.0023	0	0.1775
	Voice and data	1.0549	0.0833	0.2743	1.6790
Data	None	0.7785	0.2436	0.0283	2.0535
	12 preceding hours	0.0845	0.0037	0	0.1806
	Voice and text	0.5640	0.1242	0.0060	1.5095

Table 1. A brief summarization of entropy values.

Remarks:

1 The temporal relevancy is the dominant contributing factor to traffic predictability.

2 The contribution of spatial relevancy is much less, but it also makes sense to traffic prediction.

3 The inter-service relevancy between voice and text can be applied to the prediction problem while the one between data and the other two types can not.

4 Data traffic prediction can only depend on temporal and spatial relevancies.

Prediction Performance: The Current State of Research?

The previous sections have shown the feasibility of traffic prediction theoretically and laid a foundation for practical prediction of these three types of services. Methodologies of traffic prediction fall into two categories [5]. One is based on a fitting model (e.g. ON-OFF model, FARIMA model, mobility model, network traffic model, and alpha-stable model) to explore the traffic characteristics, such as spatial and temporal relevancies or self-similarity, and obtain the future traffic by appropriate prediction methods. The other is based on modern signal processing techniques (e.g. the principal components analysis (PCA) method, the Kalman filtering method, or the compressive sensing method[2] [13]) to capture the evolution of traffic.

Figure 4 demonstrates the prediction performance of a temporal compressive sensing method in [5]. The method takes into account the temporal similarity in traffic variations and applies modern signal processing techniques to solve the prediction problem. Specifically, it first constructs a traffic matrix using the already known traffic records in a certain number of cells, each row of which denotes the traffic variations in one cell. Afterward, the traffic matrix is augmented with a null vector, which indicates the traffic to be predicted. Consequently, the augmented matrix exhibits sparsity in two folds. In the first place, the matrix contains very few unknown entries. Second, the traffic variations are somewhat periodical, thus making the traffic matrix have few dominant eigenvalues. Therefore, the unknown entries in the matrix can be computed by the compressive sensing method. Meanwhile, in order to make a more precise prediction, the method in [5] also considers the spatial and temporal relevancies, which have been validated by entropy theory.

As Fig. 4 describes, the prediction performance in terms of the root mean square error (RMSE) is incrementally improved as the number of exploited preceding hours increases. That trend matches both the common sense and our entropy-based analysis results. Moreover, the voice traffic can be more precisely forecast, consistent with the conclusion that its temporal conditional entropy is the smallest among the three types of services. In contrast, forecasting data traffic is most challenging; it needs more prior information such as adjacent cells' traffic to obtain a precise prediction.

[2] As a signal processing technique for efficiently acquiring and reconstructing a signal, compressive sensing is renowned for finding solutions to underdetermined linear systems with relatively few measurements, by taking advantage of the sparseness or compressibility of the signal in some domain.

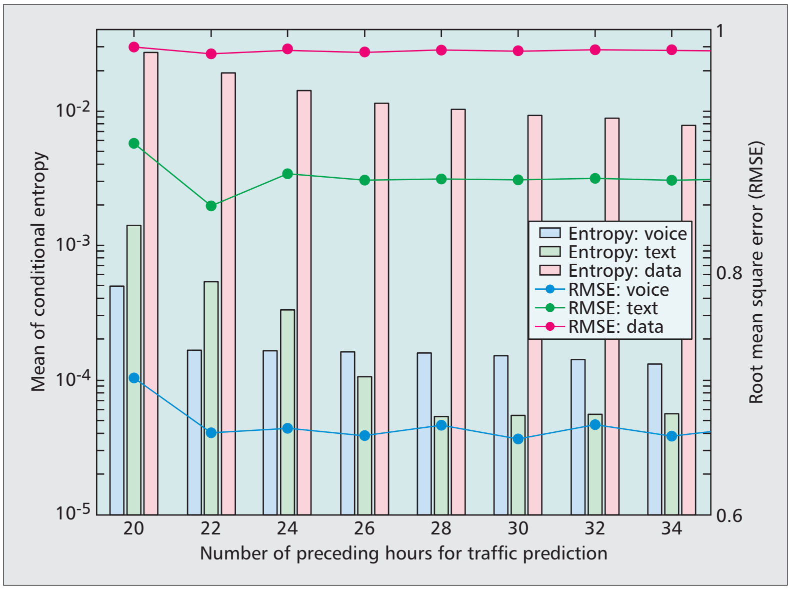

Figure 4. The root mean square error of predicted traffic versus the number of exploited preceding hours for traffic prediction.

Traffic Prediction and Future Network Architecture: Directions and Applications

We have shown in the previous section that traffic prediction is feasible both theoretically and practically. With traffic forecasting capability, it is possible for networks to be configured and managed more efficiently. For example, Niu [4] advocated establishing traffic-aware energy-efficient radio access networks, or the so-called TANGO. One of the key principles in TANGO is to make the working status of network elements (e.g. BSs) to be adaptively adjusted according to the traffic pattern. Specifically, some BSs or elements of BSs can be tuned into sleeping mode to save energy when the predicted traffic is negligible, while other BSs expand their coverage in a coordinated manner. Indeed, TANGO could be regarded as a special case of traffic-based network resource reconfiguration in SDCRANs. Owing to the flexibility of resource allocation and its considerable agility to meet explosively increasing traffic demands [14, 15], we argue that SDCRANs would be the most potentially suitable future cellular architecture, in which traffic prediction acts as one of the dominant factors for on-demand network management.

Brief Description of the Traffic-based SDCRAN Architecture

The SDCRAN architecture, which is illustrated in Fig. 5, exemplifies the typical methodology of the general software-defined core networks[3] and provides a blueprint for data plane and control plane separation in CRANs. Compared to the general SDNs, the virtualized network functions such as routers or switches are replaced by virtualized radio resources in SDCRANs, including coordinately deployed BSs and antenna systems, a shared signal processing pool and supporting systems (e.g. air conditioning), etc. Benefiting from the global view of the networks provided by this centralized control plane, the operator can allocate virtualized radio resources, implement hangovers, manage interference, and balance traffic loads [15] more effectively, thus providing a smoother user experience. Besides, the SDCRANs, which support various APIs, can implement different engines in the application layer of the control plane. Specifically, by establishing the traffic monitoring/prediction and traffic-based policy engines, the operator can sense traffic variations and make traffic-aware network management policies more flexible and adaptive.

Large-Scale Traffic-Aware Resource Management

Since the virtualized radio resources are controlled as a whole in SDCRANs, the resource management concept such as TANGO can be more effectively implemented to be adaptive to large-scale traffic variations in the context of both spatial and temporal dimensions. For example, the monitoring/prediction engine can conduct an entropy-based analysis to determine the cell usually with unstable traffic and provides the related analytical results to the policy engine. As a result, these traffic-volatile BSs could be refrained from frequently changing their working status (active or sleeping mode) when dynamic BS switching operation policies are applied.

Another case that benefits from the traffic-related engines in SDCRANs is heterogeneous RAN-sharing among multiple (virtual) network operators [14]. In that regard, based on the analysis results from the traffic monitoring/prediction engine, network operators can buy the exactly required amount of radio resources, thus saving operating expenditure while supplying on-demand capacity to their customers.

Though large-scale traffic-aware resource management promises to be viable, an accurately predicted traffic knowledge would be a prerequisite. However, as noted above, it is still challenging for state-of-the-art methods to meet the prediction accuracy requirements of timely resource management. Further improvement of prediction precision and forecast accuracy in a whole area of interest in real-time mode is required but is left as future work, due to limited space.

Small-Scale Flow-Centric Resource Allocation

This article has analyzed data traffic as a whole, without further exploring the detailed characteristics of the various applications, because of the limitations of the dataset. Indeed, data applications (e.g. HTTP browsing, instant messaging, video streaming) are distinguishable from each other because of the different characteristics of their traffic profiles and the need to meet distinctive transmission (e.g. bandwidth and quality of service (QoS)) requirements. On the other hand, the 3rd-generation cellular system (3G) introduces for each user equipment a radio resource controller (RRC) state machine, which determines radio resource usage, affecting device energy consumption and the user experience.

[3] We recommend the readers to refer to [12] and [15] for more information on SDN and SDCRAN.

Currently, the design of an RRC state machine is ad-hoc with statistically configured parameters. Therefore, if the traffic patterns of the various applications are meticulously discussed and precisely predicted, finer resource management can be provided by the policy engine. For example, if the traffic monitoring/prediction engine reports that the CRANs will experience a large number of traffic flows with loose delay constraint, these flows could be offloaded to other networks (e.g. WiFi) according to the decision of the traffic-aware policy engine. In this way the allocation of radio resources (e.g. bandwidth) will be more effective and different applications could be catered for with acceptable user experience and less energy consumption.

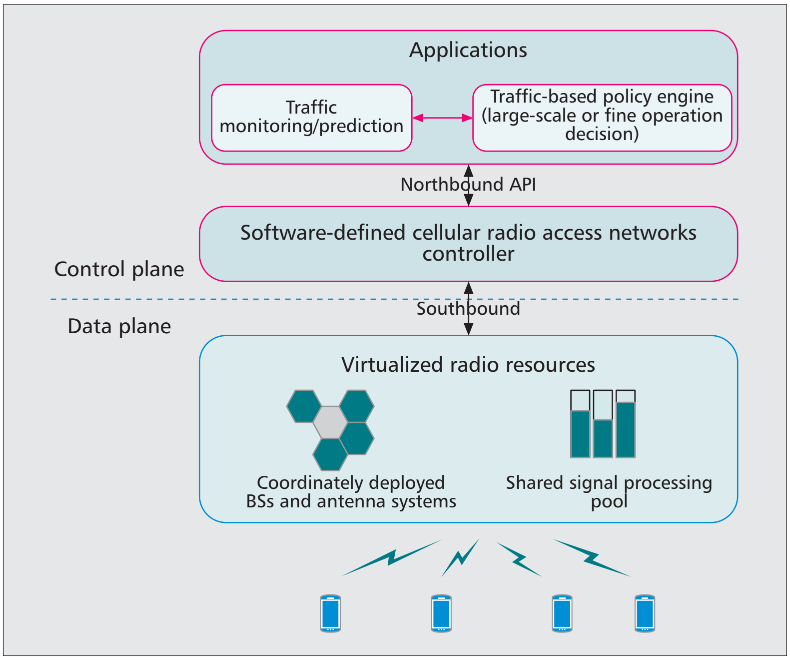

Figure 5. An illustration of traffic-based software-defined cellular radio access network (SDCRAN) architecture.

Conclusion

Predicting the traffic in cellular networks is becoming increasingly important as the explosively growing demand for radio access drives a traffic-aware energy-efficient network architecture. In this article entropy theory is exploited to analyze the feasibility of predicting traffic dynamics theoretically. The entropy-based analysis validates the spatial and temporal relevancies in all typical types of service traffic and the relevancy between voice and text traffic. Based on that, several practical prediction means and the corresponding performance are presented. Finally, the article discusses traffic-related networking applications and the contributions of traffic prediction to the design of software-defined cellular radio access networks.

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