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SERIES Y: GLOBAL INFORMATION INFRASTRUCTURE, INTERNET PROTOCOL ASPECTS, NEXT-GENERATION NETWORKS, INTERNET OF THINGS AND SMART CITIES

ITU-T Y.3650-series – Use case and application scenario for big-data-driven networking

ITU-T Y-series Recommendations – Supplement 50

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ITU-T Y-SERIES RECOMMENDATIONS

GLOBAL INFORMATION INFRASTRUCTURE, INTERNET PROTOCOL ASPECTS, NEXT-GENERATION NETWORKS, INTERNET OF THINGS AND SMART CITIES

For further details, please refer to the list of ITU-T Recommendations.

Supplement 50 to ITU-T Y-series Recommendations

ITU-T Y.3650-series – Use case and application scenario for big-data-driven networking

Summary

Big-data-driven networking (bDDN) is a type of future network framework that collects big data from networks and applications, and generates big data intelligence based on the big data; it then provides big data intelligence to facilitate smarter and autonomous network management, operation, control, optimization and security, etc.

Supplement 50 to ITU-T Y-series Recommendations presents a set of use cases and several scenarios supported by bDDN including: 1) network management; 2) network active maintenance; 3) network optimization; 4) network operation; 5) network attack prevention; 6) root cause tracking of quality of service (QoS); 7) quality of experience (QoE) improvement; 8) resource management; 9) network planning and design; 10) traffic engineering; 11) cross-layer design; 12) content delivery network (CDN); 13) network address translation (NAT) device detection; 14) bDDN in future networks; 15) bDDN in data centre networks; and 16) bDDN in industrial Internet.

History

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1 Scope

This Supplement specifies the use case and application scenario for big-data-driven networking (bDDN).

2 References

[ITU-T Y.3650] Recommendation ITU-T Y.3650 (2018), *Framework of big-data-driven networking.*

3 Definitions

3.1 Terms defined elsewhere

This Supplement uses the following term defined elsewhere:

3.1.1 big-data-driven networking (bDDN) [ITU-T Y.3650] (2018): Big-data-driven networking (bDDN) is a type of future network framework that collects big data from networks and applications, and generates big data intelligence based on the big data; it then provides big data intelligence to facilitate smarter and autonomous network management, operation, control, optimization and security, etc.

4 Abbreviations and acronyms

This Supplement uses the following abbreviations and acronyms:

2G	second Generation
3G	third Generation
4G	fourth Generation
5G	fifth Generation
ABS	Almost Blank Subframe
API	Application Programming Interface
BSS	Business Support System
bDDN	big-Data-Driven Networking
CDN	Content Delivery Network
CS	Circuit Switch
CSP	Communication Service Provider
DPI	Deep Packet Inspection
DDoS	Distributed Denial of Service
eICIC	enhanced Inter-Cell Interference Coordination
eNB	evolved Node B
GGSN	Gateway GPRS Support Node

GPRS	General Packet Radio Service
HetNet	Heterogeneous Network
IP	Internet Protocol
ISP	Internet Service Provider
IMEI	International Mobile Equipment Identity
ISDN	Integrated Services Digital Network
LTE	Long-Term Evolution
MeNB	Micro cell eNB
MNO	Mobile Network Operator
MSISDN	Mobile Subscriber International ISDN/PSTN number
NAT	Network Address Translation
PS	Packet Switch
PSTN	Public Switched Telephone Network
QoS	Quality of Service
QoE	Quality of Experience
RAN	Radio Access Network
SDN	Software-Defined Networking
SeNB	Small-cell eNB
SGSN	Service GPRS Support Node
SINR	Signal-to-Interference-plus-Noise Ratio
UE	User Equipment

5 Conventions

This Supplement uses the following conventions:

In the body of this Supplement and its appendices, the words shall, shall not, should and may sometimes appear, in which case they are to be interpreted, respectively as, is required to, is prohibited from, is recommended, and can optionally. The appearance of such phrases or keywords in an appendix or in material explicitly marked as informative are to be interpreted as having no normative intent.

6 Use cases for big-data-driven networking

6.1 Big-data-driven network management

Various kinds of data, such as those from traffic measurement, network configuration and network failure alarms, are used in managing networks. Awareness of network status can be realized by analysing configuration data and operation data with big data technologies, smart and autonomous management allowing the traditional passive management pattern to be replaced. See Figure 6-1.

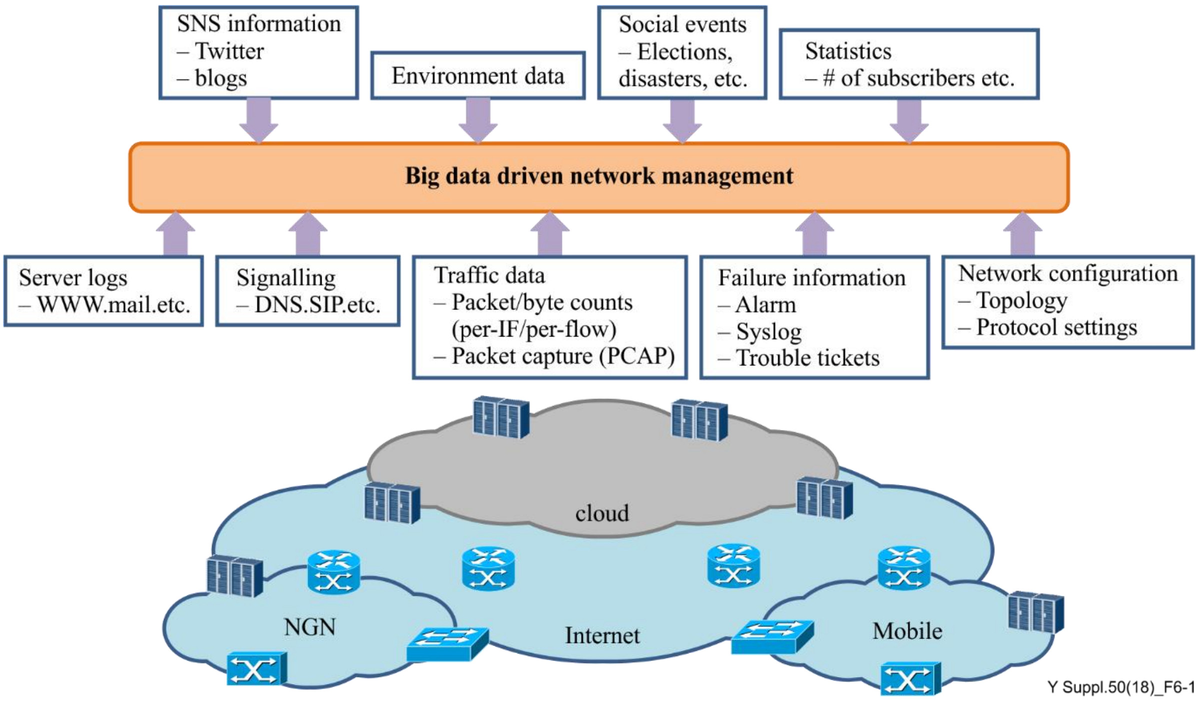

Figure 6-1 – Big-data-driven network management

6.2 Big-data-driven network active maintenance

The traditional network maintenance system that focuses on fault alarm has been unable to achieve end-to-end full coverage, whole process, real-time monitoring and analysis.

The traditional operation model is based on a customer complaint or network fault and alarm. The model cannot pre-treat customer perception. It is difficult to fundamentally guarantee and improve customer experience.

Active maintenance based on big data can quickly determine the performance of the network in the imbalance between the nodes, abnormal trend of hidden problems etc., with active network analysis based on network big data. According to such an analysis, engineers can target for exact optimization, reduce costs, improve network quality and customer satisfaction before a failure occurs.

In order to realize active user perception, deep packet analysis by telecom operators has enabled mobile communication network signalling data acquisition and analysis projects. However, the signalling data and new deep packet inspection (DPI) data volume is far larger than that of traditional data. These characteristics and data analysis can be used to promote big data thinking and technology.

Through signalling data collection and big-data analysis, user detail information can be obtained to improve user-perceived end-to-end experience by realizing active maintenance and solving problems before the user complains.

6.3 Big-data-driven network optimization

Big-data analytical techniques can provide the operator with deep insights into their networks to make informed decisions. For example, these analytical techniques can help the operator to monitor and analyse various types of data, as well as event messages, in networks.

Intelligence and important insights can be extracted from both instantaneous and historic data. Useful information, such as the correlation between user behaviour and network traffic, can help the operator not only to make decisions based on long-term strategies, but also to optimize resource allocation to minimize deployment and operational costs.

6.3.1 Big-data-driven interference coordination

Within a heterogeneous network (HetNet) that has small cells, interference among macro and small cells requires coordination in the time domain in lieu of the frequency domain, such as the enhanced inter-cell interference coordination (eICIC) scheme in long term evolution (LTE)-Advanced.

The determination of an appropriate almost blank subframe (ABS) ratio of the macro cell to the small cells depends on many factors, including the service types and traffic load in a given area. As is well known, service behaviour in small cells vary with time. Moreover, the traffic patterns of individual services also change. Thus, inter-cell interference does not remain constant. Therefore, the optimal ABS ratio essentially changes dynamically with time. In a bDDN system, network analytics can be used to optimize the allocation of radio resources. Resources can be allocated to adapt to both environmental and traffic changes based on information gained from data analytics. To enable a quick response, some bDDN optimization functions can be deployed at the micro cell eNB (MeNB), so that they can collect and analyse evolved node B (eNB) originated raw big data in real time (e.g., service and traffic feature characteristics). Consequently, the performance of each cell and users can be optimized by periodically processing raw data to obtain statistics and automatically detecting traffic variations, targeting the prediction of eICIC-optimized parameters, such as the ABS ratio. Moreover, a global optimization process can jointly optimize the location and traffic demands of multiple eNB users. For instance, a certain small-cell eNB (SeNB) can be deactivated in order to avoid interference with its nearby SeNB, which might have a larger throughput due to a higher signal-to-interference-plus-noise ratio (SINR). Additionally, a reduction in energy consumption may be another optimization objective to be considered.

6.4 Big-data-driven network operation (marketing)

By analysing user behaviour and preferences, as well as network status data, elaborate network operation can be achieved.

Analysing customer network service use behaviour is crucial to understanding traffic. It is important to understand customer objectives and their interactions in performing operations when network operations are executed.

6.4.1 Big-data-driven prediction of customer upgrade in mobile network

With the evolution of the mobile network, faster speed improves customer experience. Mobile network operators (MNOs) invite more customers to use a higher rather than lower generation mobile network. MNOs need effective methods to predict customer preferences. MNOs can then guide customers to complete a mobile network upgrade, from third generation (3G) to fourth generation (4G) or from second generation (2G) to 3G. By analysing big data of customer service use behaviour, combined with terminal and billing data, customers preferring an upgrade can be identified, and marketing operation strategy personalized. Figure 6-2 shows the architecture of big-data-driven prediction of customer upgrade in a mobile network.

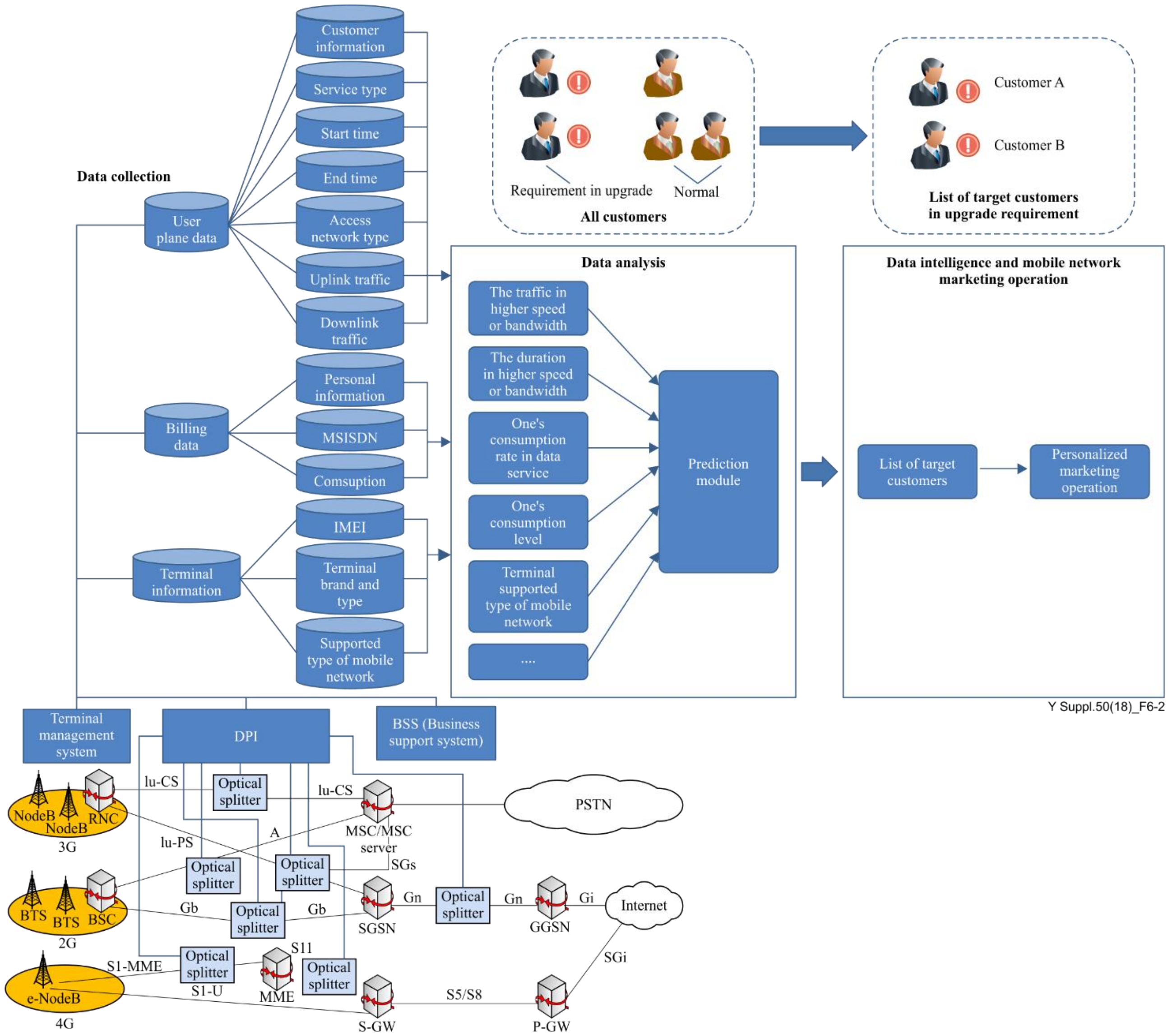

Figure 6-2 – Big-data-driven prediction of customer upgrade in mobile network

6.4.1.1 Data collection

It is useful to collect mobile user plane data, terminal information data and billing data that can be obtained through DPI, operator management systems for terminals or other external terminal management systems and the business support system (BSS) of operators.

User plane data includes the customer mobile subscriber international integrated services digital network/ public switched telephone network (ISDN/PSTN) number (MSISDN), international mobile equipment identity (IMEI), start time, end time, access network type and uplink traffic and downlink traffic for packet switch (PS) service. Furthermore, terminal information data includes IMEI, brand and type of terminal and its supported type of mobile network. In addition, billing data includes customer personal information, MSISDN and service consumption. In a word, data can record customer service use behaviour and consumption and reveal the capabilities of their terminals.

6.4.1.2 Data analysis

The data collected in clause 6.4.1.1 can be correlated to analyse customer behaviour and consumption characteristics. Indexes can be calculated, such as those for traffic and duration in higher speed or bandwidth (video, image, etc.), data service consumption rate and consumption level. Generally, the higher the values, the stronger are the preferences for upgrade. Combining data about the customer terminal type, e.g., support or not for a higher generation mobile network, can influence the likelihood of whether the customer is targeted. A prediction module can be designed to produce lists of customers requiring an upgrade.

6.4.1.3 Data intelligence and mobile network marketing operation

In marketing operation strategy, target customers in the list are guided to upgrade according to the requirement intensity represented by prediction and their current situations. For example, customers whose mobile devices support higher type of mobile network are preferentially guided to meet their upgrade preferences. For example, by big-data analysis, it is predicted that customers A and B both want to upgrade to 4G. However, the terminal of A supports 3G while that of B supports 4G. So, B is chosen first.

6.4.2 User churn prediction based on network big data

Customer churn is perhaps the biggest challenge to the telecommunications industry. A churner quits the service provided by operators and no longer yields any profit. Through analysis of network big data, operators can predict customer churn and take proactive care to prevent it.

Real-time analytics map the user journey and generate actionable insights that can allow operators to respond quickly with a "next-best offer" and convert interested prospects into customers. Data such as customer demographics, purchasing behaviour and clickstreams are combined with attributes such as location and content preferences for next best offers. Data also enable communication service providers (CSPs) to map specific customer's interactions with telecommunications operators at various stages of the lifecycle to promote tailored offerings and campaigns. Journey analytics, for example, could include a real-time analytics model pulling together two personalized offers based on customers. Such a model can allow operators to respond quickly with a user journey and to generate actionable insights. Using big data, operators build intelligence and analytics tools to proactively identify issues and fix them or offer solutions before issues impact the customer. Not only do big data provide a compelling customer experience, but also they deflect and remove the need for calls to customer care centres, thereby lowering support costs. Service providers proactively fix issues or reach out to customers to help resolve issues before they negatively impact the experience. Telecommunications operators build intelligent network big-data platforms for their broadband services to identify experience issues for their high-value customers and proactively fix those issues or engage with customers.

Given the impact of customer churn affecting the telecommunications industry today, service providers effectively use big-data analytics to bring together various data points including: quality of service (QoS); network performance; subscriber billing information; details of calls to the care centres; and social media sentiment analysis to build an effective model to predict and prevent churn. Churn prediction allows operators to launch retention campaigns that identify and then address "at risk" customers via outbound channels. For example, CSPs can proactively reach out to high-value customers, who have experienced a series of QoS issues or who share a negative sentiment regarding the service in social media, and address those issues and offer them discounts or service credits to prevent customers from defecting.

6.5 Big-data-driven network attack prevention and root cause

Network security is a big concern. Since the network plane in the bDDN architecture is vertically split into three main functional layers, potential malicious attacks can be launched on any of them. Based on the possible targets, attacks on bDDN can be classified into three categories: application layer attacks; control layer attacks; and infrastructure layer attacks, as shown in Figure 6-3. There are two methods of launching application layer attacks. One is to attack some applications; the other is to attack a northbound application programming interface (API). The controller is a potential single point of failure risk for the network, so it is a particularly attractive target for attacks on the bDDN architecture. The following methods can be used to launch control plane attacks: attacking a controller; a northbound API; or a southbound API. There are two methods of launching infrastructure plane attacks. One is to attack some switches/routers; the other is to attack a southbound API. Some attackers, such as distributed denial of service (DDoS) attackers, take advantage of botnets and other high-speed Internet access technologies, and the size of attacks has grown dramatically. Therefore, traditional data analysis methods have many difficulties in defeating these attacks.

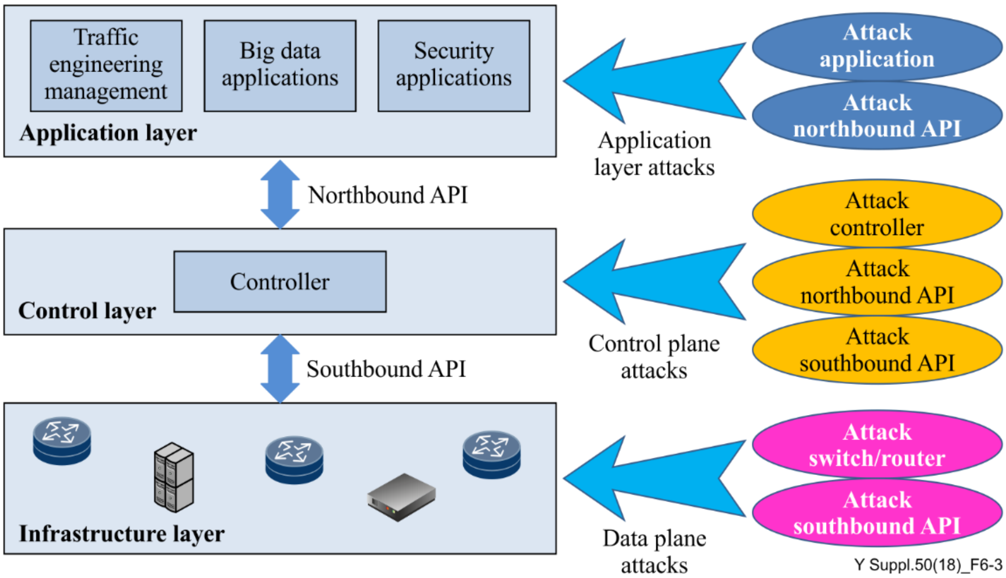

Figure 6-3 – Potential attacks on the three layers of bDDN architecture

The application of big-data analytics to mitigate security attack problems is becoming more and more attractive.

Security and safety incident advance warnings can be given by associating and analysing traffic data, user logs and system logs.

By tracking and characterizing malware threats or fraudulent transactions in real time (for neutralization), machine-learning algorithms can be implemented to effectively characterize new as-yet unknown threats. By providing a seamless correlation between the physical and virtual domains, obscure patterns (such as those that span data centres) can be identified to characterize and neutralize such threats.

Big-data analytics enable comprehensive analysis of large volumes of disparate and complex data from various sources in different formats. These data can be compared, anomaly detection performed and cyber threats combated in real time. Multi-dimensional to ultra-high-dimensional data models can be built to accurately profile the data streams online, which allows detection and even prediction of security attacks in real time. Big-data analysis can also provide correlation methods among heterogeneous security data. Furthermore, machine-learning methods for big-data analytics have the potential to successfully defend against future attackers and detect anomalies.

6.6 Big-data-driven root cause tracking of quality of service anomaly detection

The root cause tracking of network QoS anomalies is very important for service or application QoS assurance. The causes of QoS anomalies are layered, see Figure 6-4. Example of network fault events include:

– path fault event;
– device fault event;
– card fault event;
– port fault event;
– link fault event.

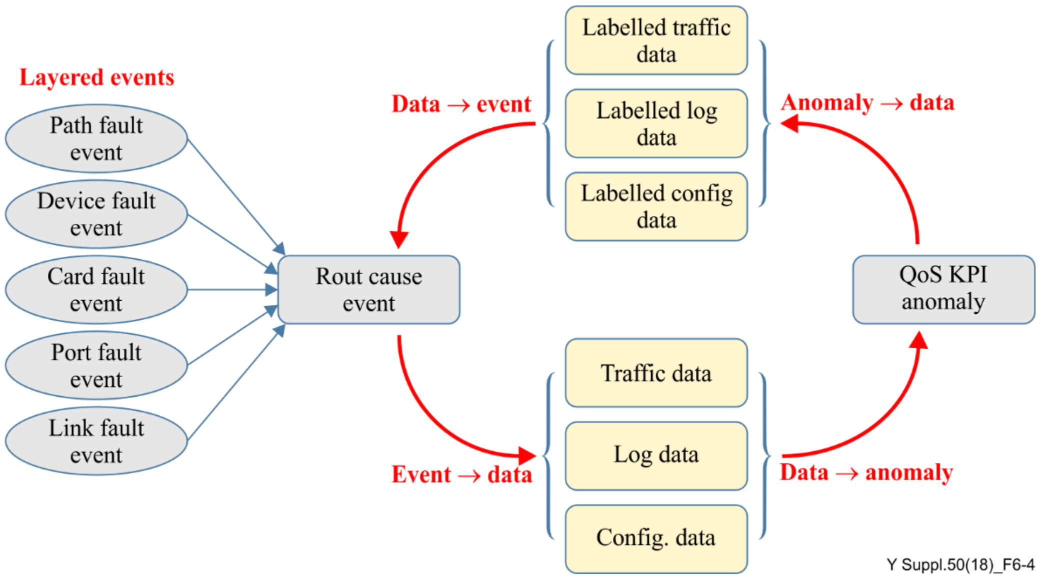

Figure 6-4 – Big-data-driven quality of service anomaly detection and root cause tracking

Network performance anomalies are network data, e.g., network traffic data, syslog data and management data. QoS anomaly network data are from network anomaly events, e.g., network attacks, protocol bugs and link up/down. Based on the analysis of multi-layer dependence and spatiotemporal dependence of network data and network events, bDDN can reversely track the root causes of network anomalies. The bDDN can clarify the positive correlations and reverse tracking mechanisms of network 'anomaly events – anomaly data – Network anomalies'. See Figure 6-5.

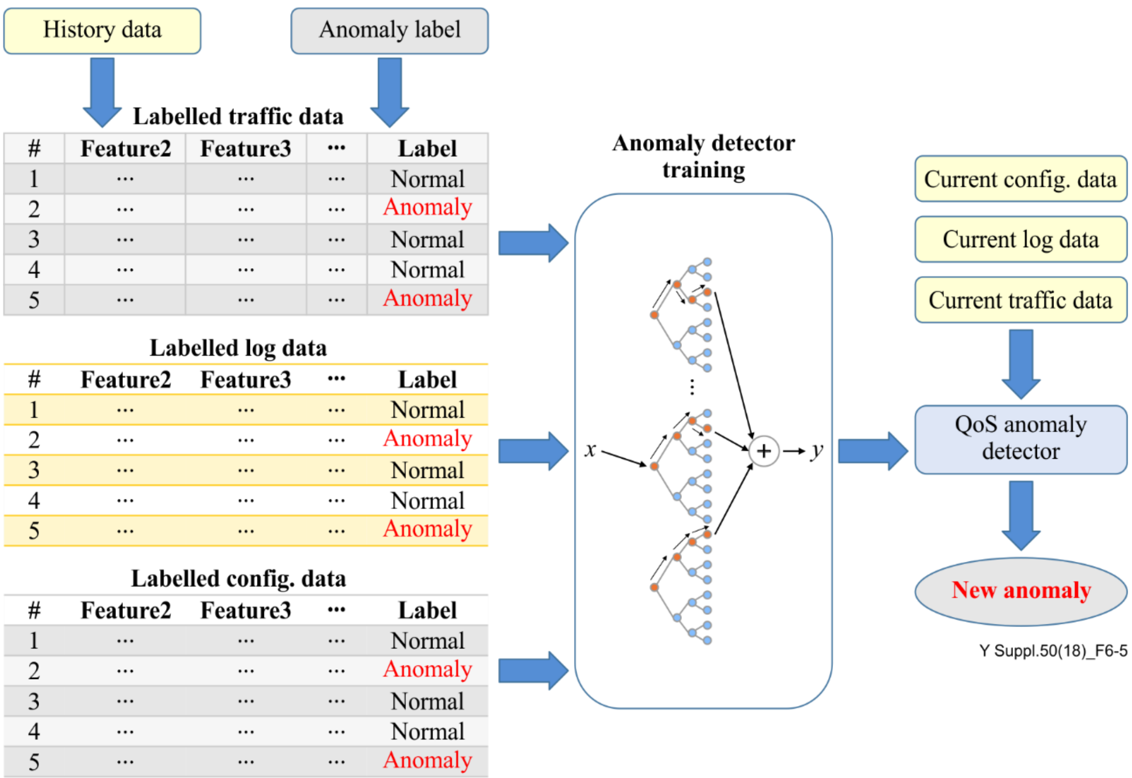

Figure 6-5 – Training of quality of service anomaly detector

6.7 Big-data-driven quality of experience/quality of service improvement

User quality of experience (QoE) can be promoted by analysing big data from network status data and user patterns.

Typically, various services and applications are managed by using a set of QoS parameters (e.g., packet loss, delay, and jitter). However, management can be more efficient when the quality as perceived by end users (i.e., QoE) is taken as the optimization objective instead of QoS. Towards this end, automatic and accurate estimation of QoE in real time is the first step. Data analytics can help with QoE modelling and monitoring in a diverse heterogeneous environment, which is essential for global network optimization.

As shown in Figure 6-6, the data needed to estimate QoE come from both the network and users. Besides the technical factors, various non-technical factors exist that may influence QoE results, including: device type; user emotion; habit; and expectation. Thus, in QoE evaluation, it is useful to create an individual profile for each user, which is a user model representing user preferences, habits and interests. A user does not usually like to spend much time answering questions to create a profile model. As an alternative, a user profile can be built and monitored using data analytics with implicit information gathered by a profile collection engine. The activities of users are tracked and compared to identify similarities and differences. For example, the output of the motion detector in the profile collection engine may include (but is not limited to) the number of clicks and scrolling on the screen. In the emotion detector, a user emotion may be extracted from a detected user behaviour with affective computing techniques. Meanwhile, network data including QoS parameters are collected through the measurement and signalling in the network. All data are stored in a database for further processing. A machine-learning engine is then used to establish the relationship between the influencing factors and the QoE through artificial intelligence. Machine-learning techniques enable ever more accurate decision-making over time, even when the data sets are incomplete or new situations arise. The analysis of large data sets leads to insights into users' real experiences, which may need to incorporate social data. Data analytics can discover what operators need to know, which impacts QoE across devices, services and network resources.

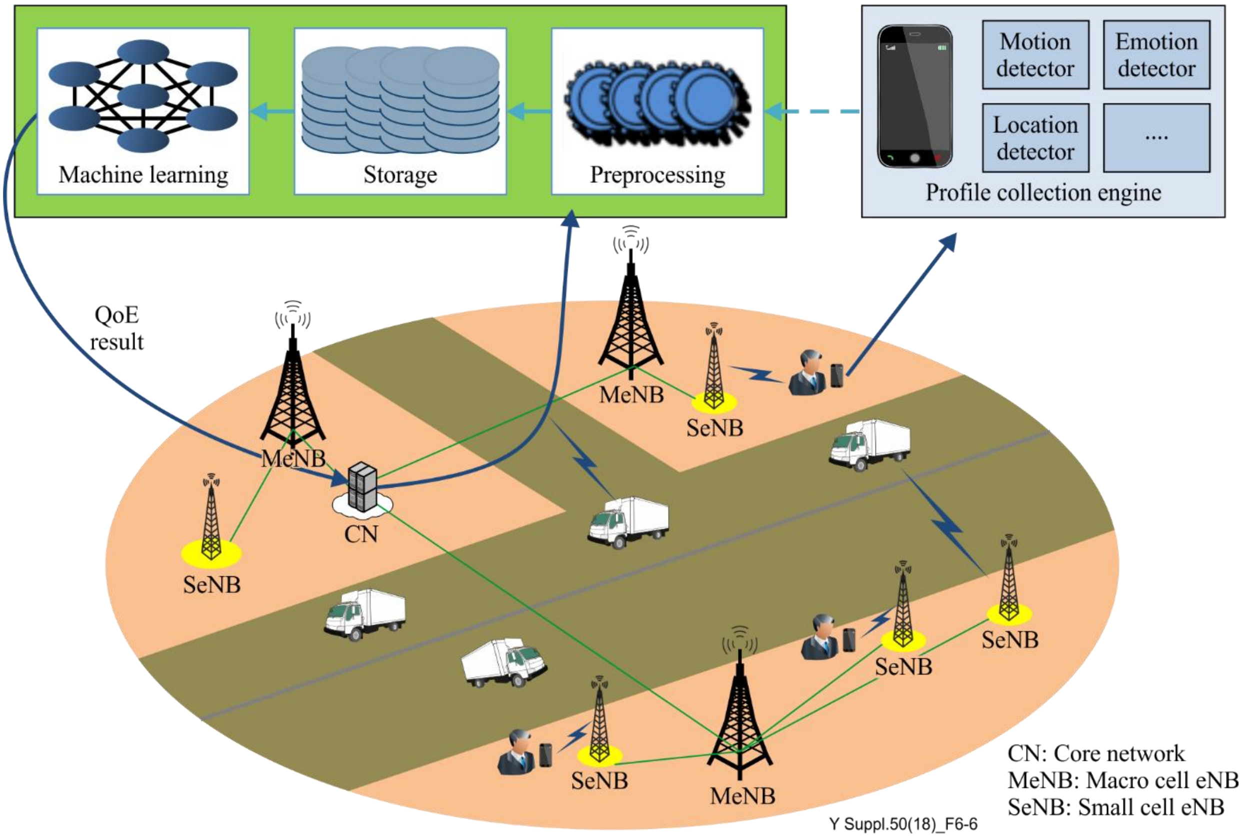

Figure 6-6 – Big-data-driven quality of experience improvement

6.8 Big-data-driven resource management

Network operators should be aware of their long-term deployment objectives in terms of network capacity, coverage, and the number and locations of base stations. They also need new resource allocation strategies in order to fulfil different traffic demands or requirements across the entire coverage area. To achieve these goals, operators have been monitoring network QoS through driving tests with smartphones. Measurement results are gathered from selected smartphones or specific driving test phones in their networks, which are analysed by specialized software. However, this is not cost-effective due to excessive consumption of time and human resources, and is also inaccurate due to the limited number of test samples.

Thus, the use of big-data analytics can provide a new way to tackle these problems. Network analytics involve monitoring and analysing real-time and history data across users, mobile networks and service providers.

Network resources can be dynamically allocated in real time by analysing network resource data, traffic data and user information.

By utilizing data analytics, changing resource requirements from one location to another in a specific period become predictable. In addition to network data, behavioural and sentiment analyses from social networks and other sources require consideration to predict where and how users may use the mobile network. For example, when a social event such as a marathon takes place in a city, some places like the streets on the race route may attract large crowds of people, resulting in potential congested traffic in these locations during the event. Hence, with this predicted information from data analytics, operators can allocate more radio resources to the hotspot in such a way that the peak traffic can be absorbed smoothly without sacrificing user QoE.

Users often travel from one place to another around the city (e.g., work in the central business district during the day and live in a suburb at night). This causes the traffic of each cell to fluctuate significantly at different times of day, which is dubbed the "tide effect." If resources are allocated to each cell with a fixed configuration, resource utilization must be underestimated, and it is difficult for users in the hotspot to obtain good QoE during peak hours. On the other hand, a great deal of resources may be wasted in idle times at low traffic locations. Current and historical data can be utilized by data analytics to predict traffic for high-density areas in the networks. Then, with the radio access network (RAN) architecture, predictive resource allocation in centralized baseband units may help to accurately serve the right place at the right time (i.e., knowing when and where peak traffic arises), causing minimum disruptions to services.

6.8.1 Big-data-driven resource allocation based on user interest

By evaluating closeness (both geographic and social) among users in the same base station, users with high closeness are categorized into a cluster. Users in the same cluster can share a wireless channel and receive the same content, which not only improves the data rate for cluster users, but also saves base station resources.

Figure 6-7 depicts the use case of big-data-driven resource allocation based on user interest.

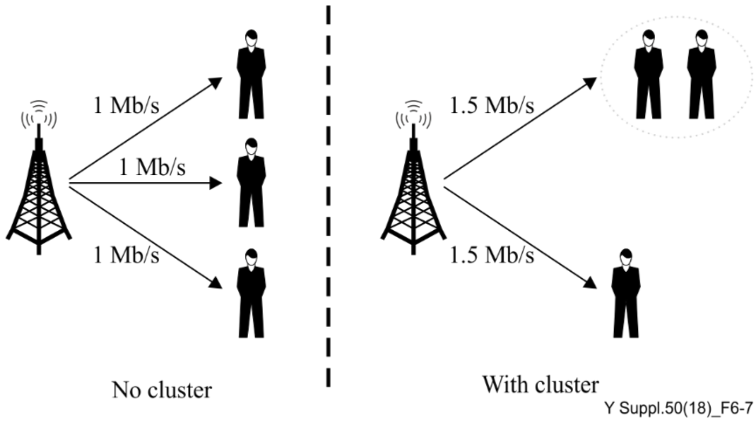

Figure 6-7 – Big-data-driven resource allocation based on user interest

Evaluating closeness (both geographic and social) among users in the same base station requires collection of the following:

1) geographic data: the location and mobility pattern of users;

2) social data: the social characters of users, including contact information and device information;

3) network data: wireless channel states, including channel fading and interference.

6.8.2 Big-data-driven resource allocation based on mobile user moving behaviour

According to mobile user moving behaviour, resources are allocated to each base station with a fixed configuration, resource utilization must be underestimated. On one hand, it is difficult for users in a hotspot to obtain good QoE during peak hours. On the other, resources may be greatly wasted in idle times at low traffic locations.

Current and historical data can be utilized by data analytics to predict traffic for high-density areas in the networks. Using the respiratory effect of the base station may help to accurately serve the right place at the right time, promoting recourse utilization.

To adjust the recourse utilization of the base station, it is necessary to collect the following:

1) network data: the wireless channel states, including channel fading and interference;

2) user data: the location and access pattern of users that can be collected from the interface between service general packet radio service (GPRS) support node (SGSN) and gateway GPRS support node (GGSN).

6.9 Big-data-driven network planning and design

In most traditional deployment cases, the sites of cells in mobile network are not optimized due to insufficient statistical data. By tracking mobile devices, their detailed activities can be recorded to provide real-time where, when and what information about mobile users in the network. A feasible solution is to make use of both network and anonymous user data including dynamic position information, and other various service features. Consequently, massive volume, velocity and variety of data need to be processed by advanced analytics techniques, which can transform the data into actionable knowledge. In order to understand traffic trends well, it is imperative to analyse the data in relation to corresponding content and events.

Given the actionable knowledge inferred from big datasets, the MNOs can make wise decisions about where and how to deploy cells in the networks. This also allows them to predict traffic trends and prepare plans for future investment.

Network design can be more efficient and reasonable with comprehensive data study of network status, external environment and various elementary issues.

Analysing customer behaviour in their use of network services is crucial to understand traffic. Thus, concurrent weather and temperature data and social event information are taken into consideration to better understand traffic.

6.9.1 Big-data-driven mobile network planning and construction based on customer experience

When mobile customers use the services provided by MNOs, big data is generated both in the user plane and signal plane. By analysing them comprehensively, actual user experience in their use of services can be determined. According to the experience of users within the same base station, a judgement can be made about whether the base station is poor. A reasonable and intelligent plan to increase quantity or expand capacity of the base station can then be made to improve mobile network quality efficiently. Figure 6-8 shows the architecture of big-data-driven mobile network planning and construction.

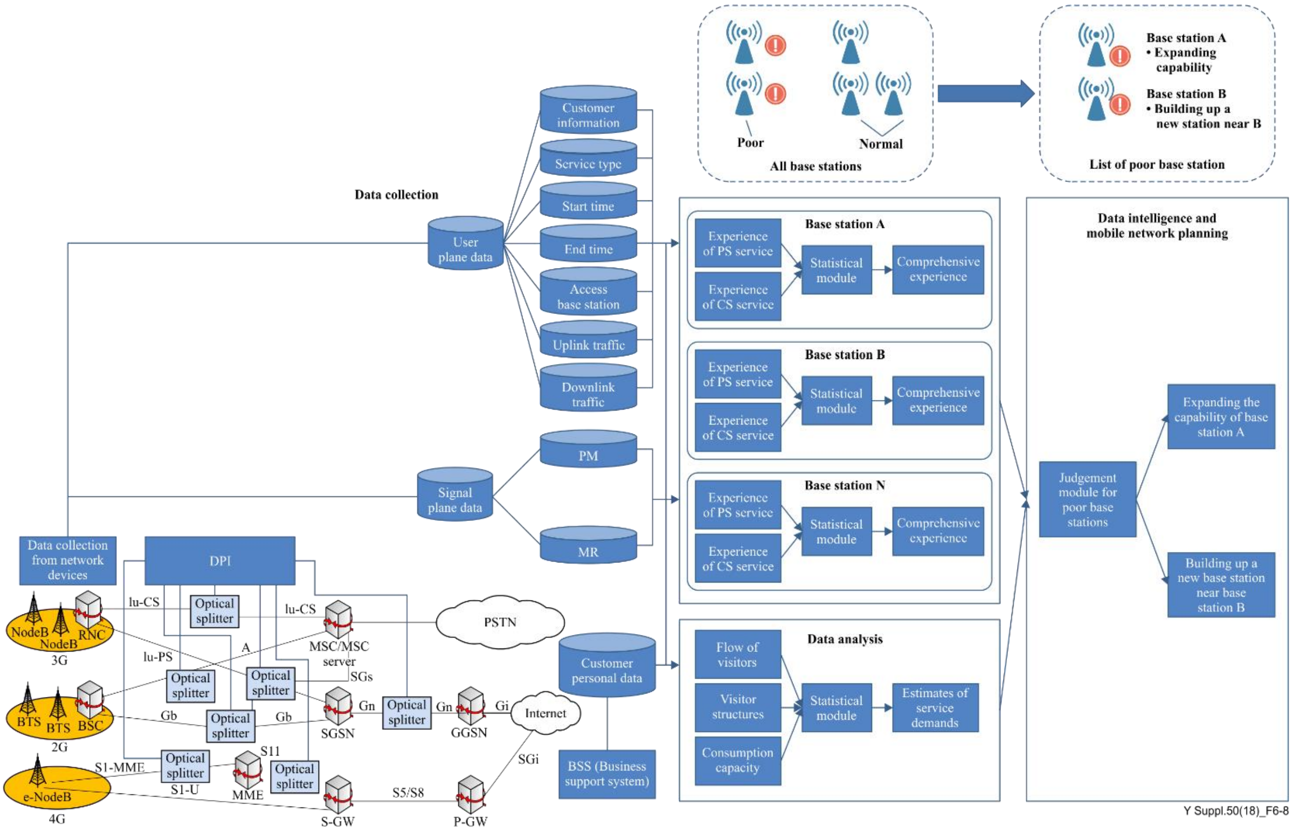

Figure 6-8 – Big-data-driven mobile network planning and construction based on customer experience

6.9.1.1 Data collection

It is useful to collect mobile user plane data and signal plane data that can be obtained through DPI and network devices; additionally, customer personal data should be extracted from the BSS.

User plane data includes the customer MSISDN, service type, start time, end time, access base station information, uplink traffic and downlink traffic for PS service.

Signal plane data includes performance measurement data and a measurement report. In a word, they can record the whole process and the access base station of all customers when they use services.

Personal data includes customer basic information (e.g., age, occupation) and consumption information (e.g., service plans).

6.9.1.2 Data analysis

Data collected in clause 6.9.1.1 can be correlated to analyse customer experience of service use. For the PS service, indexes reflecting experience, e.g., speed, time delay and success rate of service, can be calculated. Indexes can also be derived, e.g., for time delay of call and call completion rate, for the circuit switch (CS) service.

A statistical module is required for every base station to evaluate customer experience there. Additionally, the experience evaluation can be called the comprehensive experience of the base station.

Furthermore, service demand can be assessed in the coverage area of every base station to support their decision-making. Service demands can be calculated, e.g., from visitor flow, visitor type breakdown (e.g., 30% students, 20% active workers) in a specified area or service consumption capacity.

6.9.1.3 Data intelligence and mobile network planning

All base stations can be compared based on comprehensive experience, and the poor ones identified. Some statistical modules can calculate which base stations are poor. The decision to expand the capacity of poor base stations or to build new ones nearby can be made accurately based on service demand estimates.

6.10 Big-data-driven traffic engineering

Traffic engineering is an important method of optimizing network performance by dynamically analysing, predicting and regulating the behaviour of data transmitted over that network. Typical objectives of traffic engineering include balancing network load and maximizing network utilization. bDDN and big data-analytics provide a convenient and effective way to perform traffic engineering and improve network performance on a large scale. Typically, a software-defined networking (SDN) based network consists of thousands of hosts with significant bandwidth requirements. Traffic engineering in such networks is very challenging. The big-data plane in bDDN for traffic engineering is an apt solution for the following reasons:

1) it is relatively easy to obtain big data traffic and failure information via a logically centralized network controller;
2) any flow format of big traffic data with arbitrary granularity can be exploited for traffic engineering;
3) it is relatively easier to apply traffic engineering results to switches in a data centre network by modifying flow tables within the switches.

Figure 6-9 depicts a dynamic traffic engineering system architecture with SDN and big data, which consists of four components: a data centre network; an SDN controller; a traffic engineering manager; and big-data applications. In the data centre network, there are many servers and SDN switches/routers; such a network is a target network of the traffic engineering system. The SDN switches/routers in the data centre network report their big traffic data and failure status to the SDN controller through the control/data plane interface. The SDN controller aggregates and summarizes the big traffic data information collected and sends it to the big-data applications. Big-data analytics, which leverage analytical methods to obtain insights from the big traffic data, then give guidance to the traffic engineering manager, which derives the traffic engineering policies. According to these traffic engineering policies, the SDN controller changes the switching behaviour of SDN devices by updating their flow tables and turns devices and links on or off in the data centre network to minimize power consumption and link congestion.

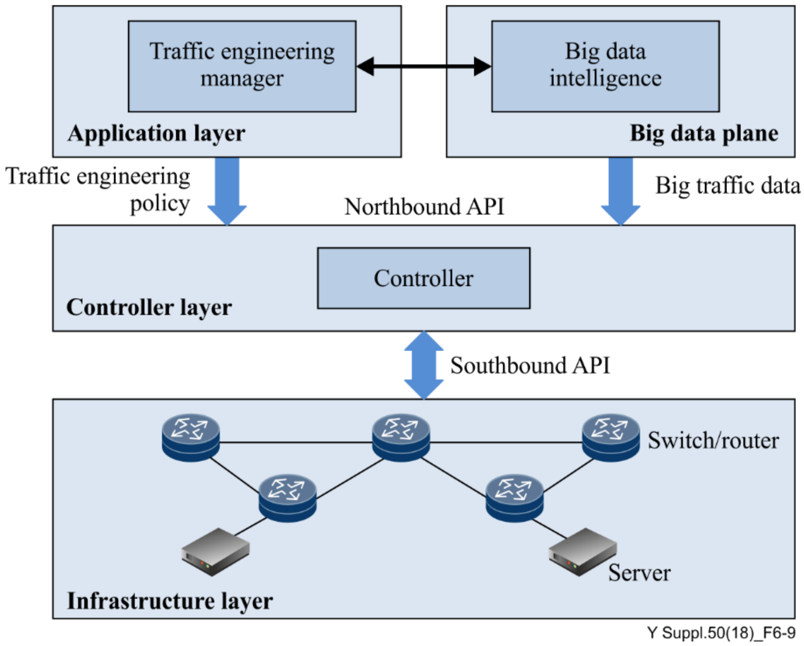

Figure 6-9 – Dynamic traffic engineering system architecture with software-defined networking and big data

6.11 Big-data-driven cross-layer design

Traditionally, networking is divided into different layers, and a set of protocols is used to communicate between adjacent layers. In traditional layered design, direct communications between non-adjacent layers are forbidden. However, recent advances in cross-layer designs show that non-adjacent layers can share information during run-time, which will result in new algorithms and significantly improved performance in networking systems. Although sharing information among different layers can improve performance, the principle of modularity is broken and the network becomes so complex that traditional approaches are inadequate to design and optimize it.

Fortunately, bDDN can benefit cross-layer design. The logically centralized controller in bDDN has a global view of the network, which enables it to obtain big data from all layers with arbitrary granularity, such as channel state information in the physical layer, packet information in the data link/network layers and application information in the application layer. Applying big data technologies to network control and management can significantly improve network control and management processes.

Therefore, cross-layer design in bDDN will be challenging. Here we present an architecture combining big data and bDDN that can facilitate the cross-layer design in bDDN with the help of big data. There are three layers in the architecture: the infrastructure layer; the data processing and control layer; and the application layer, as shown in Figure 6-10. The infrastructure layer consists of switches/routers, servers and data centre devices. The switching or routing devices transfer data packets to the next hop in accordance with forwarding rules stored in local memory. The servers in the data centre store the big data and run the tasks. In the data processing and control layer, the bDDN controller and big-data plane cooperate closely in processing the big data and making decisions together. The bDDN controller provides the big-data plane with cross-layer information from all layers, while the big-data plane provides the controller with network control strategies (physical layer parameters adaptation, resource allocation, topology construction, routing mechanisms, congestion control, etc.) to operate and optimize the performance of bDDN. Both big-data applications and networking applications run on the top of the data processing and control layer.

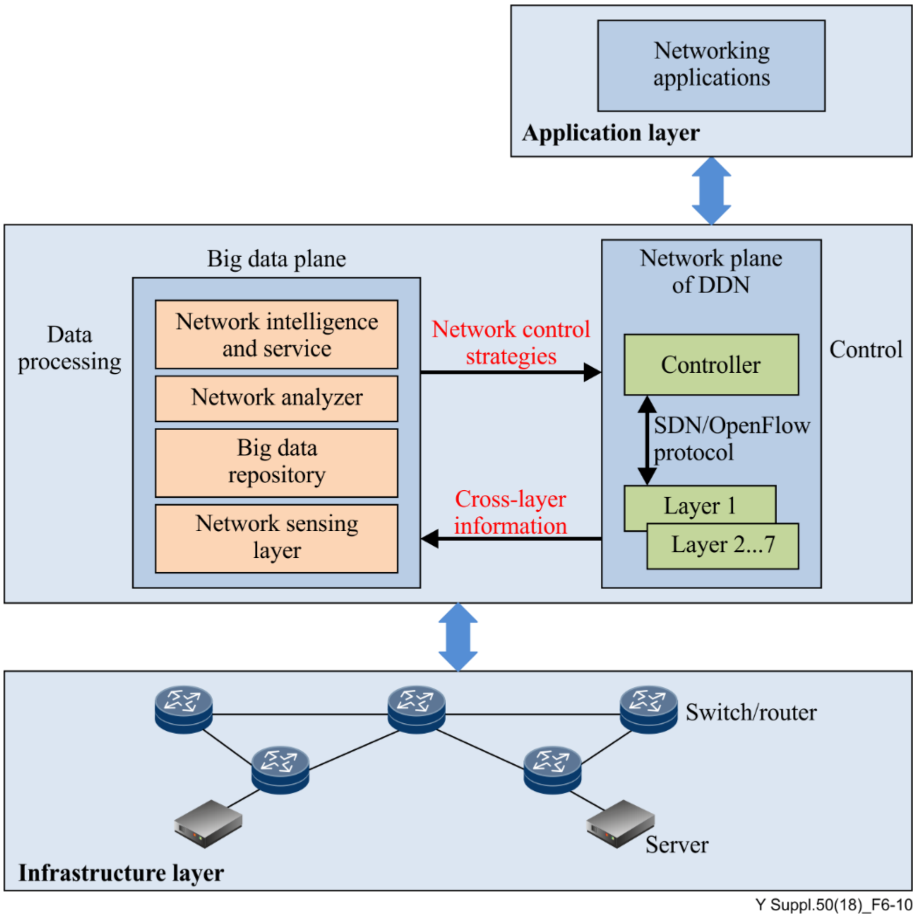

Figure 6-10 – Cross-layer design with bDDN and big data

6.12 Big-data-driven content delivery network deployment

The content delivery network (CDN) has been considered by MNOs as an efficient delivery method for popular content, such as blockbuster movies. The main purpose of having their own CDNs is to reduce operational costs while providing good support to their core businesses. The deployment of CDN based on big data technology is the most effective.

6.12.1 Big-data-driven cache server deployment in content delivery network

It is important to locate distributed cache servers in the CDN as close to the end user as possible in order to shorten response time and also reduce delivery costs, e.g., a distributed cache server working together with a central cache server in a hierarchical CDN. However, the cache access rate on the distributed cache server might be lower than that of the central cache server. Sometimes the distributed cache server even needs user data traffic to traverse the associated central cache server through the link in the event of improper placement. Therefore, it is vital to choose the optimum location for the cache servers in the hierarchical CDN.

Beside the cost of storage and streaming equipment, the features and load of traffic in a given area are among the important factors that determine the optimal placement of a cache server. After collecting data relating to all relevant factors in the coverage area over a long period of time, big-data analysis can be used as a feasible method in data analytics to help the MNOs deploy cache servers in the network.

The analytics capabilities are built into the hierarchical CDN by utilizing a collective intelligence data architecture. Each cache server has a monitor agent to collect log information. This monitor agent sends log status information to the data analytics function block, which then determines when and what content to outsource, as well as placement of the replicas.

Therefore, the data analytics function needs to analyse the data related to both content and users to accurately determine or predict content popularity.

6.12.2 Big-data-driven content scheduling in content delivery network

Content of high popularity is more likely to be placed on cache servers in RAN to improve the cache access ratio popularity, while content of low popularity can be placed on cache servers in an edge provider. The content popularity analysis depends on not only the content itself, but also users. Moreover, user mobility may cause the content in the cache to change frequently, resulting in inefficiency in content caching. Therefore, the data analytics function needs to analyse the data related to both content and users in order to accurately determine or predict content popularity.

Overall, content popularity analysis and content scheduling require collection of the following data:

1) user data: the location and access pattern of users, which can be collected from the interface between SGSN and GGSN;

2) content data: crawling from the Google or public website.

6.12.3 Content transmission control to end user of content delivery network in big-data-driven networking

Due to physical space storage, cache nodes in a mobile network are limited, while cache nodes in a fixed network specially deployed in the data centre are almost infinite. So, cache nodes in a mobile network can only store limited content. There is a requirement to transmit data among cache nodes. Figure 6-11 depicts content transmission control to the CDN end user in bDDN. The process is as follows:

1) a mobile user watches a video from the cache node deployed in the fixed network;

2) other mobile users request the same content;

3) the big-data plane, sensing the request, transfers data from cache node deployed in fixed network to the cache node deployed in the mobile network that is nearest to these mobile users;

4) mobile users get the content from the cache node deployed in the mobile network;

5) during data transmission from the fixed to the mobile network between cache nodes, the network plane controls the transmission speed and route, while the management plane also implements the charge policy according to the data transmitted.

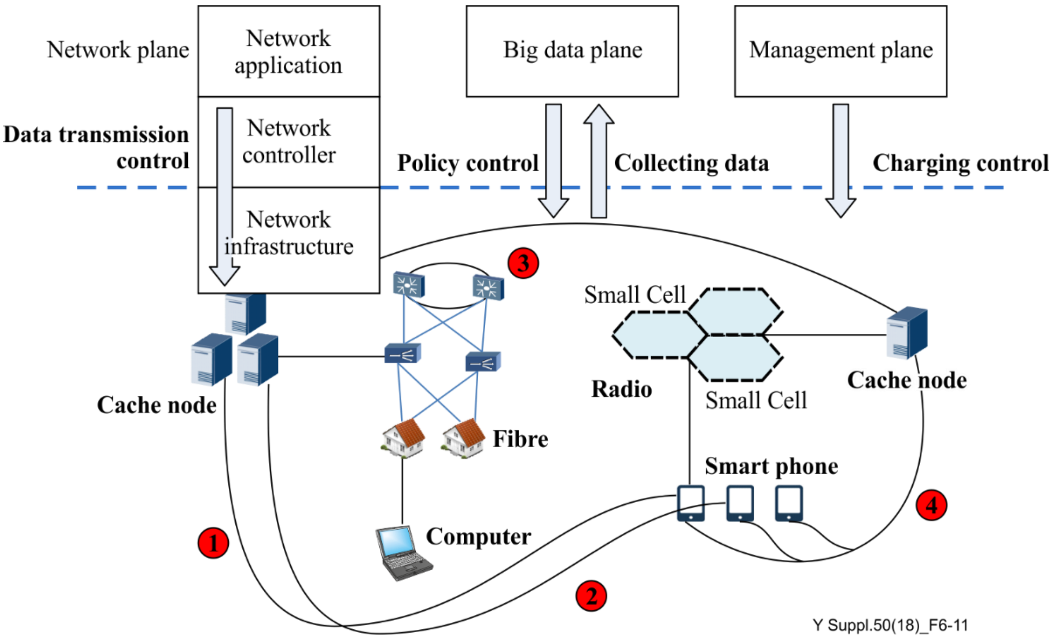

Figure 6-11 – Content transmission control to the content delivery network end user in big-data-driven networking

In this case, there are two scenarios: content transcode according to the user terminal and content transmission control between cache nodes.

1) Content transcode according to the user terminal in cache node of CDN in bDDN.

A mobile user requests a video stream from the data source. The big-data plane network sensing layer of collects radio information (e.g., cell load, link quality). To reduce time-to-start and 'best' video quality, the big data repository needs to transcode the video according to the client radio network link status (i.e., to transcode the video into a lower bit rate stream).

Also, for different types of cell phone, various types of encoding content are needed. Figure 6-12 illustrates content transcode according to the user terminal in the cache node of CDN in bDDN.

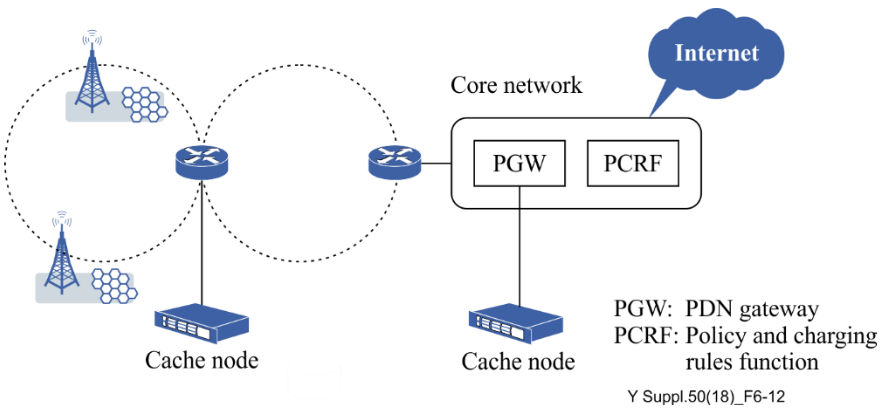

Figure 6-12 – Content transcode according to the user terminal in the content delivery network cache node in big-data-driven networking

2) Content transmission control between cache nodes of CDN in bDDN.

The network plane in the bDDN is responsible for network control and adjustment. When the cache nodes are deployed in the bDDN, the network plane needs to enhance control of the overlay network between the cache nodes and control the data transmission between the cache nodes according to the network state.

The big-data plane collects all data from the network infrastructure and analyses it according to the network data (including the network status forecast). When the CN1 wants to send a huge data volume to CN3 (which will take a long time), the big-data plane of bDDN computes and forecasts the physical link status between the routers in addition to forecasting the virtual link (overlay link) status between the cache nodes. If the virtual link is much better for the data transmission, the data are transferred over the virtual links. Figure 6-13 depicts content transmission control between cache nodes of CDN in bDDN.

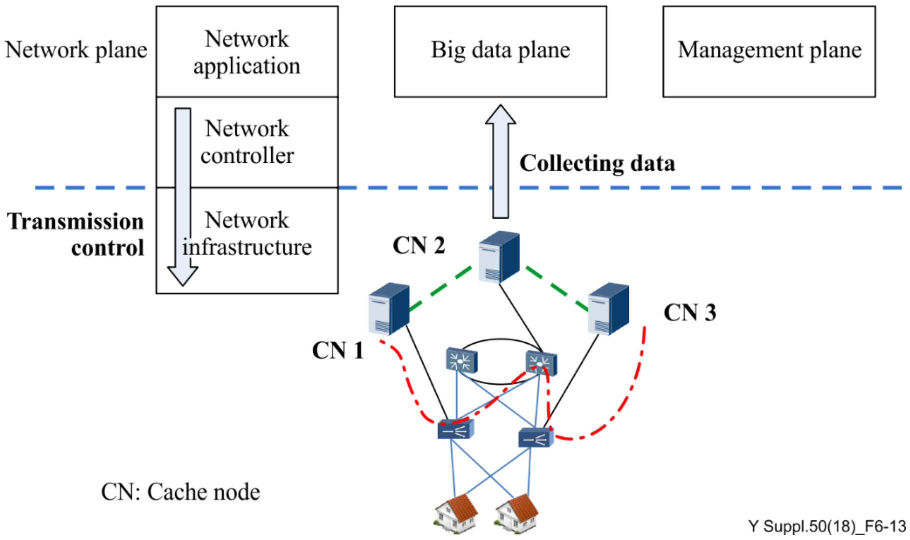

Figure 6-13 – Content transmission control between the content delivery network cache nodes in big-data-driven networking

Case 6.13 Big-data-driven NAT devices detection

For a number of reasons, including the shortage of Internet protocol version 4 (IPv4) addresses, many locations are connected to the Internet by means of network address translation (NAT) devices. A NAT box uses a very small number of IP addresses – perhaps just one – but can act as a relay for many different hosts behind it. NAT hides the internal network structure from the external network. On one hand, it offers access to illicit terminal facilities, causing potential threats to the network; on the other hand, users can also privately share networks through NAT, which directly harm the interests of network operators. Effective detection of NAT devices plays an important role in network security and control, network operation and management.

A big-data- and machine-learning-driven NAT devices detection method is shown in Figure 6-14. This is a kind of supervised machine-learning method for NAT device detection. First, the training set requires set-up. In order to identify application traffic and web browser traffic, the application signature Lib and the web signature Lib are set up. The IP addresses of known NAT devices are collected, the network traffic is identified by matching traffic of known IP addresses and the application signature Lib or the web signature Lib. Then the identified traffic data are used as the training data for the C5.0 machine-learning algorithm. After training, the C5.0 algorithm acts as the detector to identify the IP as a NAT device or not. The features are chosen of application number (the application number of accessed by the IP), application type number (application are classified into types, e.g., video, shopping; the application type number is the number of different application types that the IP accessed), application duration (the time duration that the user IP accessed the application),web browser times (the total number of times that the user IP accessed the web), web type number (webs are also classified into different types, .g., news web, sport web, business web) and web browser duration (the length of time during which the user IP accessed the website), because these features are very different for the NAT device (with multi users behind) and non-NAT IP address (single user). The detailed process is as follows: first, the identified NAT IP traffic data is matched with the application Lib and the Web Lib. The application number, application type number, application duration, web browser times, web type number and web browser duration are selected as features for training set construction. Then the training set is used to construct a decision tree according to the C5.0 decision tree model. A decision tree is a decision support tool that uses a tree-like graph or model of decisions and their possible consequences, including chance event outcomes, resource costs, and utility. The decision trees generated can be used for classification, and for this reason, they are often referred to as statistical classifiers.

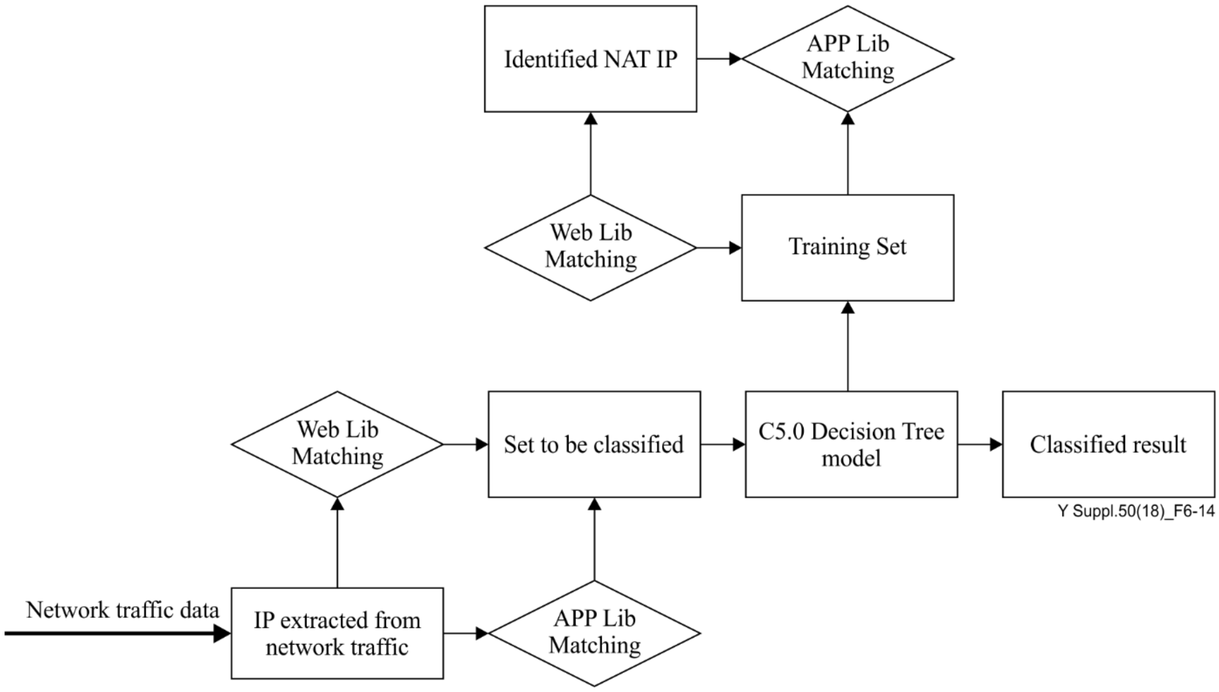

Figure 6-14 – Big-data-driven NAT devices detection based on the C5.0 decision tree

Then the IP address to be classified is extracted from the input network traffic. The traffic data are matched with the Web Lib and the APP Lib. The set to be classified is constructed and input to the C5.0 decision tree; NAT devices can then be identified with high confidence.

7 Application scenario for big-data-driven networking

7.1 Big-data-driven networking in future network (including fifth generation)

A massive number of mobile phones are in wide use and produce huge amounts of data every day. This profoundly impacts society and social interaction as well as creating tremendous challenges for MNOs. The volume, velocity and variety of data from both mobile users and communication networks have been exploding exponentially. Therefore, big data are already in our mobile life and will be further entrenched in the future network (including fifth generation (5G)). See Figure 7-1.

The big-data plane of bDDN can provide MNOs with deep insights into their networks before making informed decisions. For example, these analytical techniques can help MNOs monitor and analyse various types of data, as well as event messages in networks. Intelligence and important insights can be extracted from both instantaneous and historic data. Useful information, such as the correlation between user behaviours and network traffic, can help MNOs to not only make decisions based on long-term strategies, but also optimize resource allocation to minimize deployment and operational costs. Furthermore, MNOs are expected to play a key role in the standardization of the future network. However, a critical challenge is to understand the requirements of utilizing big-data analytics to provide user services with personalized QoE and to enable highly efficient resource utilization in the future network.

Big data in the future network need to be extensively analysed in order to retrieve relevant and valid information. Big data provide unprecedented opportunities for MNOs to understand the behaviour and requirements of mobile users, which in turn allow for intelligent real-time decision-making in a wide range of applications. By analysing these data, the future network can provide and support different smart services. However, the nature of big data presents vast challenges in relation to data mining, mobile sensing and knowledge discovery. New technologies are required to handle big data in a highly scalable, cost-effective and fault-tolerant fashion.

In order to enhance operational efficiency in network infrastructure under varying environments, MNOs are encouraged to adjust network traffic requirements and improve resource allocation efficiency using intelligence and analytics based on big data.

The collection of big data can be achieved from user equipment (UE), the RAN, the core network and Internet service providers (ISPs). The events that occur at UEs are collected either through user applications or via control signalling. At the RAN eNB, the cell-level data (including the signalling exchanged over the air) and instantaneous measurement reports are collected by DPI technology. Meanwhile, MNOs possess huge amounts of data obtained by DPI technology relating to user bearers or services in the core network. When the cell size becomes smaller in the HetNet, the number of nodes B increases. As this trend continues, network data may explode and impose a great burden on data collection.

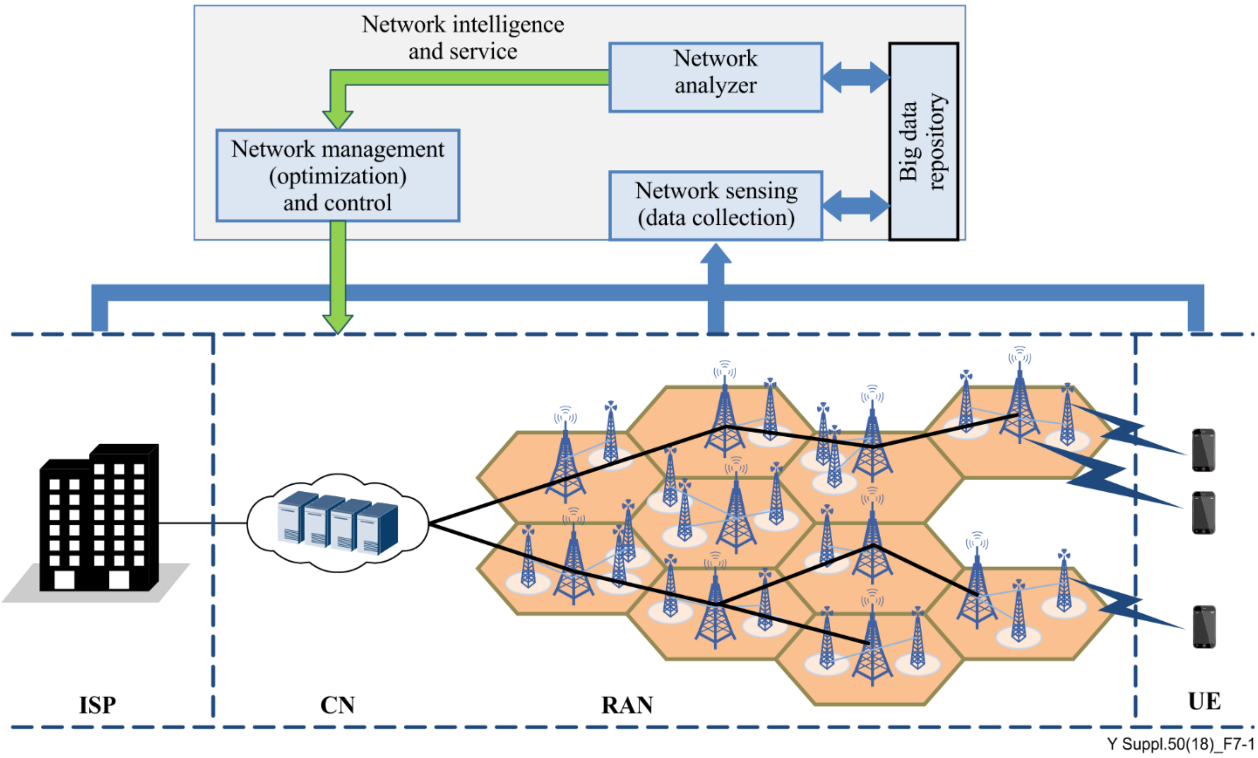

Figure 7-1 – Big-data-driven networking in the future network (including 5G)

Furthermore, big data storage infrastructure needs to have scalable capacity as well as scalable performance. Thus, storage management needs to be simple and efficient so that storing and sorting big data can be achieved easily. After data are collected and stored, another big challenge for MNOs is how to process such huge volumes of data. The collected data are multi-source, heterogeneous, real-time and voluminous. For this reason, data analytics and knowledge extraction techniques are required to process the data and convert it into actionable knowledge. Consequently, this knowledge can be used to design adaptive schemes for network optimization.

Data analytics enable MNOs to manage networks and provide services to customers in a systematic manner; not only the network measurements, but also the application/service status for each region can be monitored and analysed over time.

The big-data plane in bDDN is capable of analysing big data to identify problems, and to decide what or how to optimize the appropriate level (e.g., the user, cell or service). The improvement measures based on optimization results are then implemented by the control functions in the RAN. Moreover, user-level optimization can be performed. For users closely located in the same cell, optimization can be customized for each user depending on their service class. Furthermore, the big-data plane functions can predict traffic variations either in a local area or over the network coverage and eventually help to improve network and user performance.

7.2 Big-data-driven networking in data centre networks

Data centres have gained popularity among service providers and network operators. This has been a cause of concern for data centre networks because these applications require high-bandwidth low-latency low-energy-consumption networks.

bDDN is a promising solution for maximal resource utilization in data centres.

Figure 7-2 depicts an architecture of intra- and inter-data-centre networks with bDDN, which also includes three parts: the infrastructure; big-data plane; and network controller. In the infrastructure, there are switches and servers in the intra-data-centre network. The different data centres are connected through routers over an IP network, which forms the intra-data-centre network. In the control layer, there are several network controllers to manage the intra-data-centre switches or the inter-data-centre routers. The data processing modules schedule data processing. All network controllers are controlled by a single network controller, while all data processing modules are controlled by a big-data plane of bDDN.

The network controller and data processing of bDDN are regarded as a hybrid controller, which is the "brain" of the network.

The big-data plane in bDDN is responsible for collecting all data from server and network device (switch and router). Through the analytics of these big data, bDDN can get the information about application characteristics and network conditions.

The bDDN can provide dynamic bandwidth adjustment, QoS policy and security policy for the application.

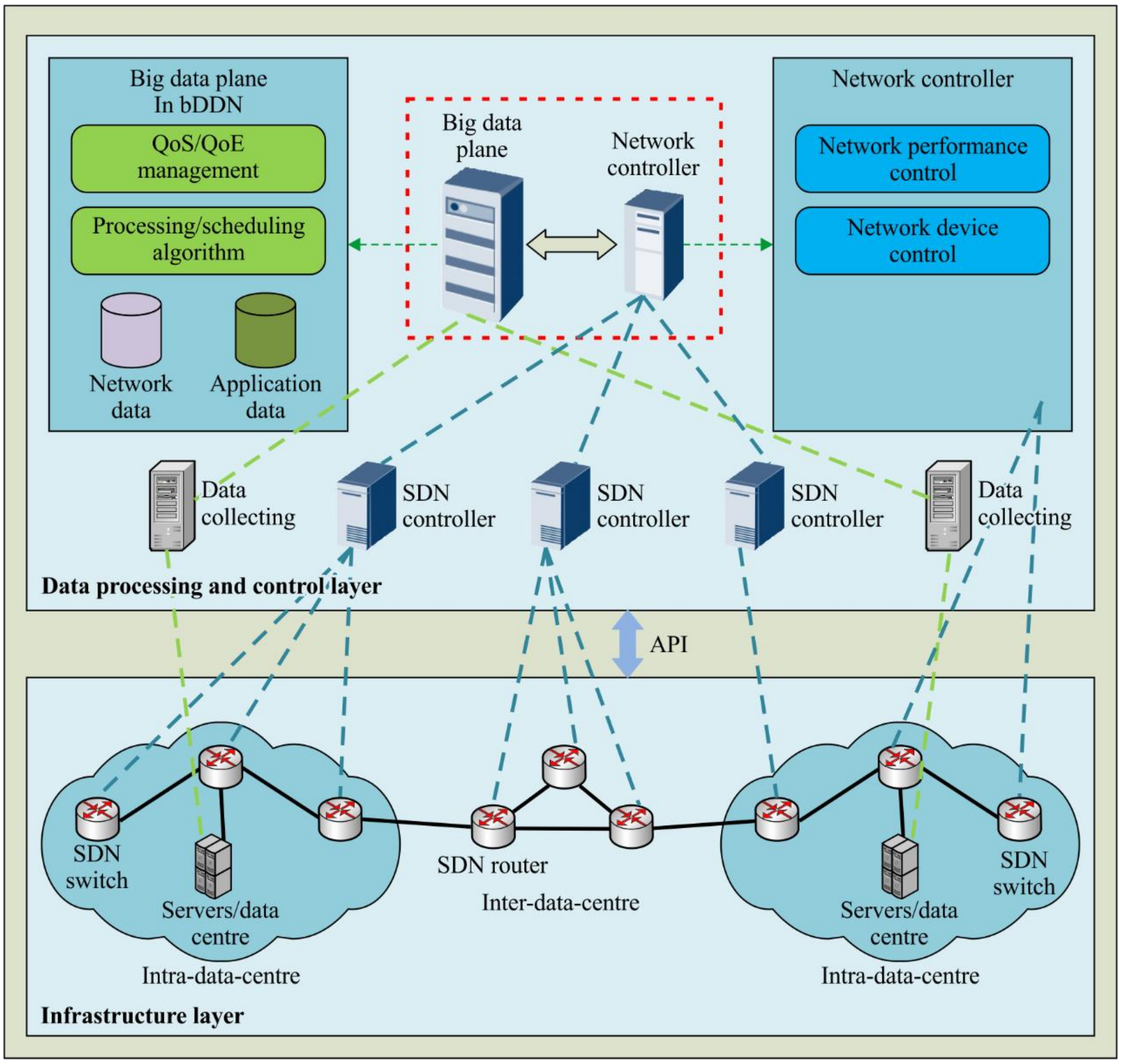

Figure 7-2 – bDDN in data centre network scenario

7.3 Big-data-driven networking in the industrial Internet

The core of the industrial Internet is data-driven intelligence based on full inter-connection. Network, data and security are common basis and support from both an industrial and an Internet view.

It is obvious that the network is the cornerstone of the industrial Internet, meanwhile data can drive and enhance industrial intelligence. On the other hand, security is a necessary feature of the industrial Internet. Therefore, network, data and security are necessary to the industrial Internet.

Figure 7-3 depicts an example of a reference architecture for the industrial Internet. In such a reference architecture, network view, data view and security view are the basis of the industrial Internet, while the application view is the capability exposure of the industrial Internet.

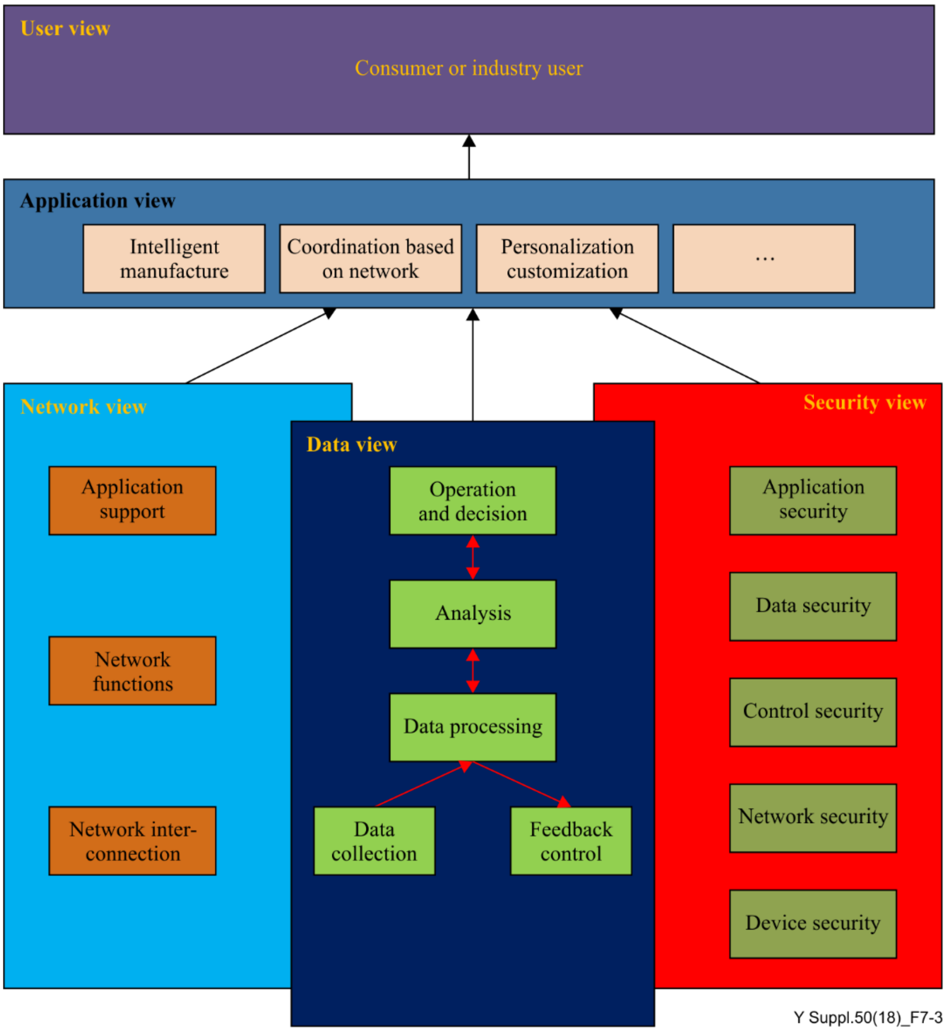

Figure 7-3 – Example reference architecture for the industrial Internet

bDDN can be applied in the industrial Internet. Figure 7-4 depicts the scenario in which bDDN is convergent with the industrial Internet.

BDDN has three planes:

– network plane;

– big-data plane;

– management plane.

The industrial Internet includes the following views (among others):

– network view;

– data view;

– security view.

From Figure 7-4, the bDDN network plane can be convergent with the industrial Internet network view and the bDDN big-data plane can interwork with the industrial Internet data view. In the meantime, the bDDN management plane can implement functions of the industrial Internet security view and provide support to the data view.

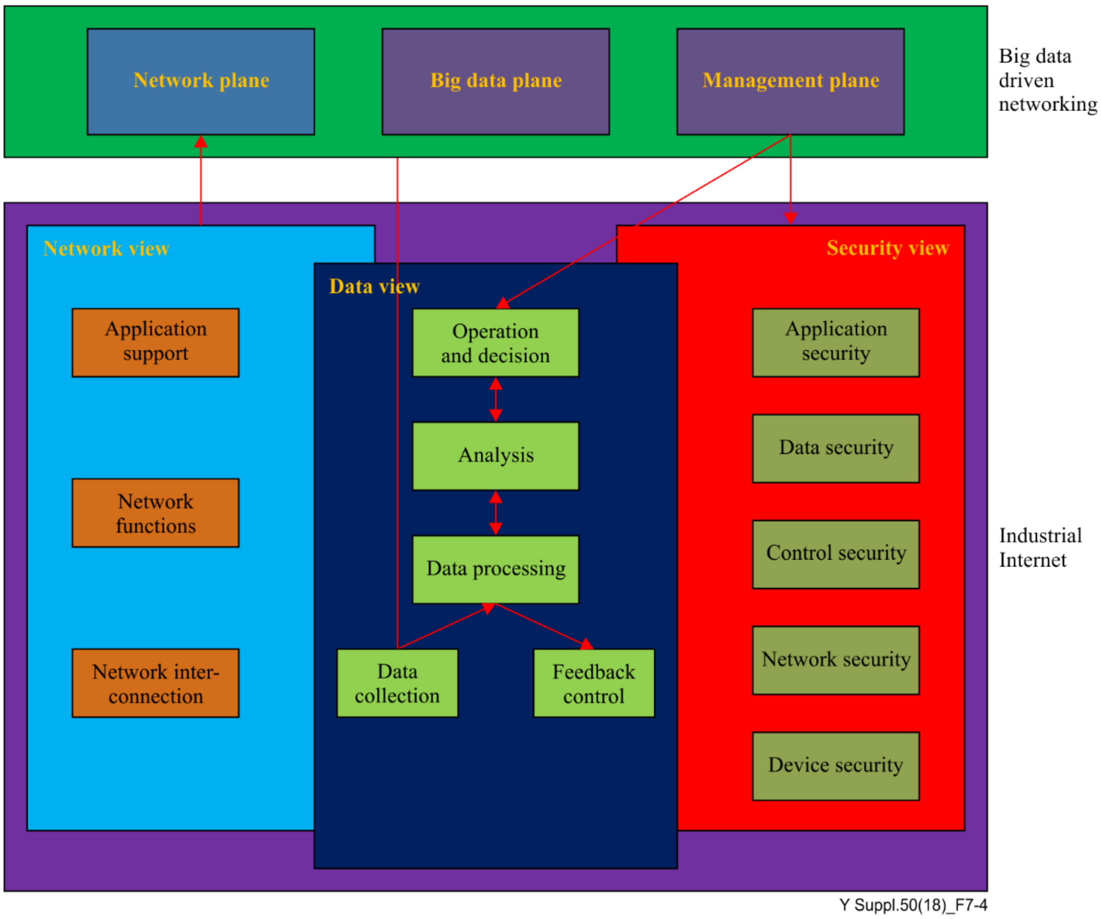

Figure 7-4 – Big-data-driven networking applied in the industrial Internet

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