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5G-enhanced smart grid services
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5G-Enhanced Smart Grid Services

The advanced services that will be offered by future smart grids call for a tight integration between power systems and communication networks. To enable enhanced power grid monitoring, effective demand side management, and appropriate charging and discharging coordination of electric vehicles, huge amount of data, with stringent quality-of-service requirements, need to be transferred among different entities of the grid in real-time. The currently existing networks are incapable of handling this volume of traffic in a flexible, scalable, and dynamic way. Fortunately, the novel concepts of 5G networks such as network slicing, cloud computing, software defined networking, and network function virtualization offer several attractive features that perfectly fit the communication requirements of the smart grid services. Through this chapter, we aim to shed the light on the 5G key concepts and how they can be extremely beneficial in supporting the advanced smart grid services. This chapter first introduces the smart grid environment and discusses some of the future services that will be supported in the future smart grids. These services are broadly classified into two categories, namely data collection and management services that target enhanced grid monitoring capabilities, and control and operation services that deal with demand side management and electric

vehicle charging and discharging coordination. Then, we illustrate how the 5G novel concepts of cloud computing, software defined networking, and network function virtualization can be employed to provide flexible, scalable, and secure services in the smart grid. Future research directions are finally discussed to deal with the open challenging issues.

0.1. Introduction

The past decade has witnessed a revolutionary transformation in the power grid infrastructure, management, and operation to enable efficient, reliable, sustainable, clean, and secure electric grid. Traditionally, the power grid followed a centralized generation scheme, where electricity is generated in distant large power plants (bulk generators) and then carried for several kilometers through a transmission grid to be delivered to the end customers via the distribution grid. Such a traditional system relies on few sensors that are distributed across the grid to carry some information back to the grid operator in order to take limited control actions. As a result, the traditional power grid depends on manual monitoring and restoration mechanisms, and hence, may suffer from occasional failures and blackouts. The introduction of modern concepts and the integration of the power grid with advanced communication networks paved the way for a smart power grid that promises an enhanced electric grid operation.

Distributed generation is a key concept that has been introduced in the smart grid. Through this concept, power generation is enabled in the distribution grid via small-scale distributed generators (DGs). These DGs can be dispatchable units that run on non-renewable fuel (e.g., diesel and gas) or re-

newable DG units such as solar panels and wind turbines. Hence, the customers can generate their own electricity at their premises. As a result of installing such DG units within the distribution grid, a new paradigm has been introduced in the smart grid, namely the microgrid. The smart grid can be regarded as a collection of microgrids. Each microgrid presents a set of DG units, energy storage systems (ESSs), and loads. Electricity now can flow either from the bulk generators to the microgrid or can be sold from the customers in the microgrid back to the electric utility company. Hence, the smart grid enables two-way flow of electricity. To ensure more efficient and reliable operation of the smart grid, a massive number of sensors are deployed throughout the power grid, which presents better observability of the grid, and as a result, pervasive control actions can be taken. These control actions can be transmitted autonomously from the grid control center on timely manner to eliminate grid failures and blackouts and present a more resilient operation of the grid via advanced self-monitoring and self-healing mechanisms. Hence, unlike the traditional grid, the smart grid relies on two-way flow of information and electricity to enhance the overall performance of the electricity sector. Thanks to the two-way flow of information, new concepts such as demand-side management (DSM) is introduced in the smart grid. In specific, through price control or direct load control (DLC), the grid operator can reduce the peak power demand in the grid, which is known as peak shaving. As a result, in the smart grid, the load will follow the available generation rather than the traditional approach where the generation used to follow the load. Hence, expensive grid expansion plans can be deferred, which saves future investments. Furthermore, due to the enhanced control mechanisms, new electric loads, i.e., electric vehicles (EVs) and ESS units, can be introduced to the grid with minimal impact. This is

possible because of novel charging and discharging coordination mechanisms.

It is evident from the above discussion that many of the aforementioned novel functionalities of the smart grid are possible thanks to the tight integration between the power grid and the communication networks. In general, there exists two types of smart grid services that require communication network support, as follows: 1) Data collection and management service, which is concerned with collecting the readings from the massive number of sensors that are deployed across the grid and the meters within the customers' premises and exchanging this data among different entities of the grid for decision making and 2) Control and operation service, which is responsible for reaching optimal control actions either for emergency mitigation or for ensuring efficient normal operation of the grid, as in DSM and EV charging and discharging coordination decisions. Given the nature of these two services, the following key requirements must be available in communication networks in order to provide the necessary support: 1) Massive access: this is essential in order to be able to collect the readings from all the sensors and meters deployed within the smart grid. These connections are clearly not human-to-human connections, but mainly machine-to-machine and machine-to-human communications. It should be highlighted that such a massive access for metering data collection should be done with very high reliability, i.e., to ensure a packet loss ratio (PLR) below 1 percent, and 2) Ultra-low latency: this is necessary for ensuring that emergency control actions are taken at a proper time. Unfortunately, the 4G networks are unable to provide such low latency even at light load conditions. In specific, experimental results have proven that the 4G LTE radio networks can achieve 15-20 milli-second in the uplink and down to 4 millisecond in the downlink for a PLR of 10^{-1} Cosovic et al. [2017]. To achieve an improved PLR of 10^{-5} , the

latency has to be increased to 40-60 millisecond. In addition, the 4G networks are not designed to support such massive machine-type connections, also with high reliability. Furthermore, in 4G networks, all the aforementioned smart grid services will be supported on the same network along with other type of services, e.g., human-to-human communications. The 4G networks present the same support and network functions to all kind of services regardless of their requirements. In turn, this does not meet the service isolation and differentiation that should be available in the network supporting the smart grid services.

On the other hand, the key concepts that are introduced in the 5G networks present a perfect match to the communication requirements of the smart grid services. Among the three service scenarios defined in the 5G networks, two service scenarios fit very well the smart grid service requirements. In specific, the massive machine type communication (mMTC) and the ultra-reliability low-latency communication (URLLC) scenarios present a perfect fit for the communication requirements of the data collection and control services of the smart grid, respectively. The mMTC service supports a massive access of machines, namely, up to 10 million connections/square meter Telecom et al. [2018]. In addition, the URLLC service supports applications with stringent latency requirements down to 1 milli-second with extremely high-reliability Telecom et al. [2018]. More importantly, the concept of network slicing that is introduced in 5G networks is able to construct different (virtual) network entities that are logically isolated and hence can support different applications on the same network without interfering with each other. As a result, two network slices for mMTC and URLLC can be dedicated to support data collection and control services in the smart grid, while the same physical network can

also be supporting other applications and industries. Furthermore, the 5G key concepts of network function virtualization (NFV), software-defined networking (SDN), and cloud computing offer a more efficient and flexible way for handling the smart grid big data and reaching optimal operational decisions in a timely manner.

The objective of this chapter is to shed the light on the 5G key concepts and how they can be extremely beneficial in supporting the smart grid services for data collection and control services. Towards this objective, we first present an overview of smart grid fundamentals with a special focus on data collection via smart meters (SMs) and phasor measurement units (PMUs) and the operation decision making for DSM and EV charging and discharging coordination. Then, we highlight the 5G key concepts in terms of network slicing, NFV, SDN, and cloud computing. Based on these foundations, the rest of the chapter discusses a set of application scenarios where the 5G key concepts play a vital role in supporting the smart grid data collection and control services. Finally, future research directions are defined.

0.2. Smart Grid Services and Communication Requirements

This section presents an overview of some of the key concepts in the smart grid and the communication requirements of different smart grid services. A brief summary is also presented for sake of completeness to discuss 5G fundamental concepts that help in addressing the communication requirements of the smart grid services.

0.2.1. Smart Grid Fundamentals

This subsection presents an overview of data collection and control services in smart grids. Specifically, we briefly discuss some issues related to SMs and PMUs for data collection in smart grids. Also, we present the key principles related to control services in smart grid for DSM and EV charging and discharging coordination.

0.2.1.1. Data Collection and Management Services

The advanced functionalities to be offered by the smart grid are possible thanks to the sophisticated monitoring system that is expected to exist in the smart grid. Such a system monitors various components within the grid and provides continuous measurements from these components to reflect their current status, which presents sufficient information for the grid operator to take necessary optimal control actions in a timely manner. In providing this information, the monitoring system relies on a massive number of SMs and PMUs that are installed at various locations in the power grid Kayastha et al. [2014].

The first location where such meters are needed is at the generation units in order to monitor the electricity generation in terms of the amount of injected power and frequency. This is necessary to measure the power quality throughout the grid. Also, this helps in ensuring the balance between both supply and demand. These meters will be of vital importance at the DG units such as wind turbines and solar panels that are installed at the customers' premises to guarantee voltage and frequency stability within the power grid. Furthermore, these meters are needed for billing purposes when a customer sells the electricity generated at his/her DG unit back to the grid. The second location where meters are needed is at the ESS units in order to measure the

batteries state-of-charge (SOC). With the presence of many renewable-based DG units, and given the intermittent nature of such units, a frequent update of the SOC of the ESS units within the microgrid is needed so as to guarantee a balance between supply and demand.

In addition, SMs and sensors/actuators with two-way communication capabilities should be widely distributed across the transmission and distribution networks of the smart grid. Such devices measure the power flow within the buses and monitor substations, transformers, capacitor banks, etc. Using the power flow measurements across the grid, a state estimation process takes place at the smart grid control unit to determine the voltage phase angles at the buses (assuming a unity magnitude in a DC state estimation process). On the other hand, advanced PMUs can directly measure the voltage phase angles at different buses and these readings are synchronized using the global positioning system (GPS) radio clock Fang et al. [2012]. In general, given the voltage values at different buses, voltage stability can be guaranteed within the grid and over-voltage and under-voltage situations can be alleviated.

The last location where SMs are needed is at the customers' premises in order to monitor the energy consumption. Such SMs are part of the advanced metering infrastructure (AMI), which includes SMs, communication networks, and meter data management systems (MDMS). Home SMs are able to provide precise readings that are recorded/displayed at the meter and also reported to the electricity utility company every 5, 15, or 30 minutes. This is extremely beneficial for the customers to monitor their energy consumption and as a result control their consumption pattern for a reduced electricity bill. Furthermore, this information is used by the electric utility company for automatic billing. An AMI testbed for monitoring of energy consumption in a residential unit is

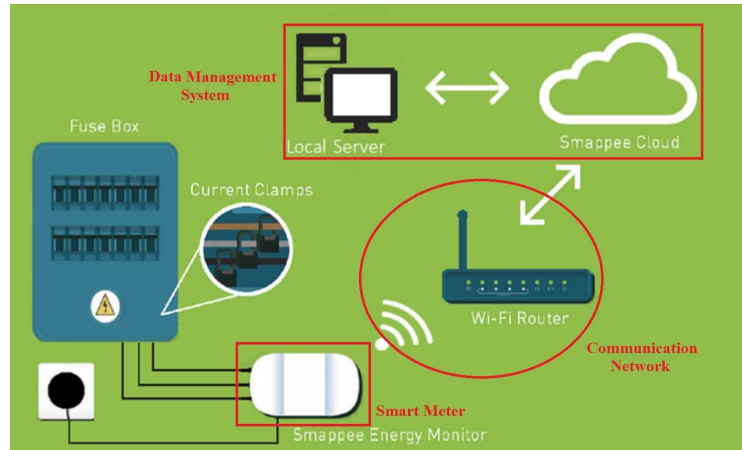


Figure 1: Illustration of an AMI testbed Alrawi et al. [2018].

shown in Figure 1. A 3-phase Smappee energy monitoring device is installed on the main circuit panel of the house. Clamp meters are utilized to measure the current flow. To power the monitoring device, a plug-in power supply is used and the Smappee device determines the voltage drop across the power supply. Using the voltage and current parameters, the energy consumption data of the house is calculated every 5 minutes. The Smappee device is connected to the internet via WiFi. The energy consumption data of the house can be accessed through the Smappee cloud for real-time monitoring and archival records are also saved at a local server. In this testbed, the Smappee device, WiFi connection, and Smappee cloud and local server represent the SM, communication network, and MDMS of the AMI. Figure 2 shows the monthly average energy consumption data that is monitored by the AMI testbed in the period from July to November 2017. It can be noticed from the results that there is a significant difference in the energy consumption between summer months such as July and August and winter months such as November. Such a difference is mainly due to the heavy dependence on air-conditioning during the

hot summer months. This difference is almost up to 6 kW power consumption, which opens the room for a great energy saving if appropriate DSM program is adopted during the summer months while considering the customers' comfort level. The two-way communication capabilities of these SMs enable active interaction between the customers and the electricity utility company. As a result, peak load reduction techniques can be implemented for instance via real-time pricing mechanisms, which is extremely beneficial for the grid operator in order to defer unnecessary grid expansion plans. In this case, when a peak load is expected by the grid operator, a high electricity price signal is sent to the SM, and as a result the customer is encouraged to reduce his/her electricity consumption for a reduced electricity bill. In addition, advanced SMs are also able to control the operation of smart appliances within the customer premises. Hence, effective DLC program can be implemented where a control signal is sent from the grid operator to the customer's SM in order to adjust or defer the operation of a device or to switch it off as a means to peak load shaving in exchange for some monetary incentives. This kind of interaction is part of the smart home paradigm. Furthermore, thanks to the continuous monitoring of the customers' energy consumption, SMs provide an effective means to detect electricity thefts.

Deployment plans of SMs in different countries reveal that a massive number of such devices is either already installed or will be installed in the near future Sun et al. [2016]. For instance, in USA, over 36 million SMs are already installed since 2010. In China, 230 million SMs are installed since 2015. Moreover, 150 million SMs are planned to be installed in India by 2025. With the regular reporting of such meter readings, massive connections are expected. In addition, these SMs open the door to several security and privacy threats

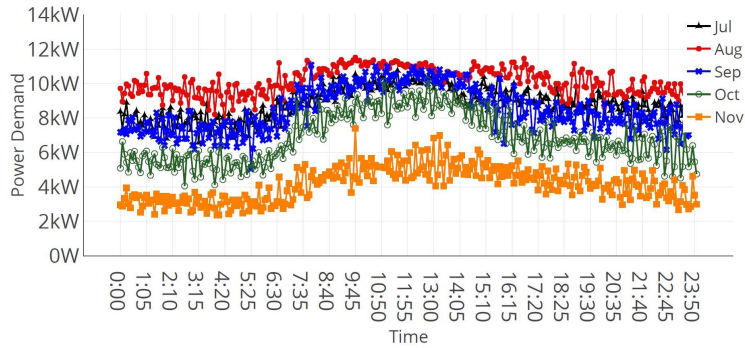


Figure 2: Collected energy consumption data from a residential unit using the AMI testbed Alrawi et al. [2018].

Mohassel et al. [2014]. In specific, frequent measurements of the customers' power consumptions (e.g., every 5 minutes) enable eavesdroppers to analyze the customers' habits and hence provide information on whether a customer is currently at home or not. This information can be misused by burglars for instance. In addition, since SMs can control the smart appliances within the customer's house for DSM, an attacker might hack into the SMs, and hence, control such smart appliances. Furthermore, electricity theft attacks can now be launched in a cyber manner, where a malicious user hacks into the SM and manipulates the integrity of the SM readings in order to reduce his/her electricity bill. The massive access requirement and the associated data management issues along with the security and privacy challenges of SMs, sensors, and actuators are well addressed by the 5G communication networks as will be discussed shortly.

0.2.1.2. Control and Operation Services

In this subsection, we focus on two control and operation services in smart grid, namely, DSM and EV charging and discharging coordination.

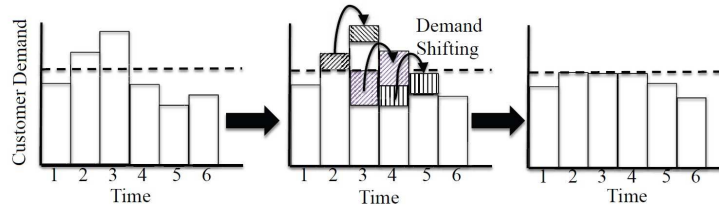


Figure 3: Illustration of peak load shifting in DSM.

Demand Side Management

DSM refers to a set of methods and strategies that are applied by the grid operator in order to modify the customers' energy demands. Such an approach is adopted to reduce the peak load within the grid, and hence, cope up with the limited energy production, as shown in Figure 3. Consequently, in the future smart grid, energy demands will follow the generation, rather than the traditional approach where the generation used to follow the energy demands. This is possible due to the two-way communications within the smart grid that promotes customer-utility interaction and enables more efficient energy usage.

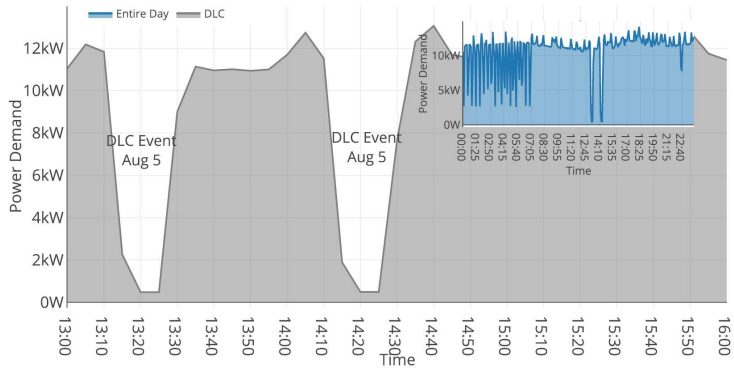
DSM presents several benefits including economic advantages, reduced greenhouse gas (GHG) emissions, and improved grid resiliency and power quality Bayram and Koc [2017]. In specific, both the utilities and the customers benefit from the economic advantages of DSM. First, the customers enjoy monetary incentives and differentiated tariffs for shifting their peak hour demand. Furthermore, by reducing the peak demand in the grid, the required upgrades to cater for the increased demand will be postponed and may now occur gradually over time, which in turn saves future investments. In addition, DSM offers a great opportunity to cut the GHG emissions since most of the pollutant electricity generation units are employed during the peak load hours, which can be alleviated using effective DSM strategies. Moreover, intelligent DSM techniques will help in reducing the mean service interruption duration, which

will further protect the loads against short-term effects such as voltage spikes, dips, and surges. Consequently, both grid resiliency and power quality will be improved.

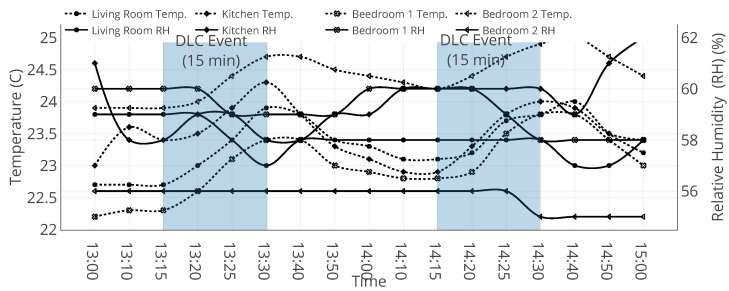
In order to develop a mathematical formulation for the DSM strategies, mathematical models of electric loads are required. In general, electric loads convert electricity into another form of energy that is deemed useful for the customers. Based on their physical properties, electric loads can be classified into resistive, inductive, capacitive, non-linear, and composite types Bayram and Koc [2017]. Resistive loads convert electric energy into heat, as in incandescent lights, ovens, toasters, and heaters. Such resistive loads usually follow on-off models, where the load draws fixed power during the on state and zero or minimal amount of power is drawn during the off state. On the other hand, inductive loads convert electric energy into motion using AC motors, as in refrigerators, vacuum cleaners, and air conditioners. These loads follow on-off decay models, where the power drawn during the on state reaches a stable level after a decay rate μ . Non-linear loads such as TV sets, computers, and fluorescent lights draw current that does not follow a sinusoidal pattern. Composite loads include more than one type of electric properties, as in the refrigerator which can be a composite of inductive load (for the compressor) and resistive load (for the door lights). In household units, it is assumed that there does not exist capacitive loads. The main goal behind a DSM program is to shift the on state of certain loads to off-peak hours and also to adjust the power drawn during this on state. To achieve this goal, the electric loads can be classified into three main classes, as follows: 1) Inelastic loads: Such loads are essential to meet the customers' comfort, and hence, shifting or reducing energy consumption of these loads are usually avoided. This class of loads includes lighting, TV, com-

puters, refrigerators, and cooking appliances. 2) Shiftable loads: These loads are flexible in a sense that they can be deferred and rescheduled for operation during off-peak hours. The deferral period of the operation of such appliances depends on customer preference, and in general, elastic loads can be further categorized into two subgroups. The first subgroup of loads represents delay sensitive appliances whose operation must be completed by a hard deadline, as in EV charging that should be complete within a specific duration set by the customer. The second subgroup represents delay tolerant appliances that do not present hard deadlines that must be met, as in deferring the washing and drying of the customer clothes until all other essential jobs are completed. 3) Adjustable loads: These loads have controllable power consumption pattern, as in air conditioners where the amount of consumed power can be adjusted by controlling the target cooling temperature. Overall, shiftable and adjustable loads offer a trade-off between the customers' comfort level and the resulting reduction in consumed power.

DSM strategies can be broadly classified into two groups, namely price-based mechanisms and DLC mechanisms. In price-based mechanisms, different tariffs are adopted by the grid operator so that the customers are encouraged to shift and adjust their power consumptions from high peak period to off-peak periods. In this context, different pricing schemes are proposed in the literature, which include static pricing schemes as in time-of-use (TOU) pricing and critical peak pricing (CPP), and dynamic pricing schemes such as real-time pricing (RTP). Specifically, TOU rates divide the day into peak, mid-peak, and off-peak periods and a fixed rate are calculated for each period. In CPP rates, the customers pay the highest price during critical load periods, and for the rest of the periods, CPP acts exactly the same as TOU. In RTP, the



(a) Energy consumption during DLC event



(b) Indoor temperature and humidity

Figure 4: Periodic 15-minutes DLC events Bayram et al. [2017].

tariffs are computed on an hourly basis and a pricing signal is delivered to the customers either an hour-ahead or a day ahead. It is clear that price-based DSM mechanisms are based on the interaction between the customers and the utility where the customers respond to the expected high tariffs by reducing their peak load via shifting and/or adjusting their loads. On the other hand, DLC mechanisms enable the utility to directly control the customers' appliances through shifting and adjusting the energy consumption in return for monetary incentives that are offered to the customers. Hence, the customer signs an agreement (contract) with the utility company to enable them to control his/her appliances in exchange for a differentiated tariff for instance. Such

a control should also respect the customers' preferences and comfort levels. Consider for instance periodic DLC events that control the operation of air conditioning appliances in a household during the summer months. From Figure 4a, the switch-off period of the air-conditioning appliances is 15-minutes, that is repeated periodically. As shown in Figure 4b, the increase in the temperature as a result of the DLC switch-off events never exceeds 25 degrees due to the short DLC duration. The amount of saved energy can be high if such an event is repeated periodically over the day. Such an approach achieves a balance between the amount of saved energy and the customer's comfort level, which is measured by the corresponding increase in the temperature and humidity as a result of switching off the air conditioning appliances.

To design effective DSM strategies, an optimization problem is formulated. The objective function of this optimization problem should account for several factors such as: the electricity cost, distribution system losses, customer comfort level, carbon emission level, and reaching a target load profile. Hence, usually such problems are formulated as multi-objective optimization problems. Several constraints must be satisfied while solving the DSM optimization problem including: 1) the load constraints in terms of the lower and upper levels of the appliance power consumption, 2) the comfort level of the customer corresponding to the load deferral and/or adjustment, 3) load types, namely inelastic, delay sensitive, delay tolerant, or adjustable loads, 4) generation constraints and/or supply-demand match constraint. Hence, the DSM strategy aims to optimize the defined multi-objective function while satisfying the aforementioned constraints. Such optimization problems can be solved in one-shot, and hence, represents a day-ahead scheduling problem, or can be solved in multi-stages where a subproblem is solved every 15 minutes interval

for real-time scheduling.

Electric Vehicles Charging and discharging Coordination

Recently, there has been a growing interest to electrify the transportation sector. Such a trend is driven by the economic and environmental advantages of the EVs. Specifically, it has been estimated that an EV costs only \$30 per kilometer compared with its gasoline-fueled counterpart that costs \$173 per kilometer Motors. Furthermore, it has been reported that EVs that completely rely on rechargeable batteries can reduce the GHG emissions by 70%, which presents a positive environmental impact. The aforementioned advantages have motivated the wide deployment of EVs. It has been estimated that at least 500,000 high-capable EVs will be on Canadian roads by 2018 Canada [2010]. Furthermore, reports have indicated that the EV penetration level will reach 35% - 62% in the period 2020 - 2050 Institute.

In general, an EV charging process that is not effectively managed presents a potential risk to the power grid, even at low EV penetration level. Clustered EVs in specific geographical areas lead to a significant stress on the local power distribution system. Such an additional load, if not appropriately managed, results in increased power losses, power quality problems, phase imbalances, fuse blowouts, and transformer degradation Liu et al. [2011], Shaaban et al. [2014a]. Two approaches can be adopted to deal with the EV additional load. The first approach relies on upgrading the power system infrastructure or installing DG units to satisfy the excess power demand Shaaban et al. [2014b]. The second approach is based on coordinated EV charging that controls the charging demand either by deferring the EV charging request or controlling the EV arrival rate to the charging facility Liang et al. [2014]. The objective is to avoid the peak load coincidence for both regular loads (i.e., commercial,

industrial, and residential loads) and EV loads. Coordinated EV charging is more appealing to the grid operators since it does not require big investment. In literature, two categories of charging coordination can be distinguished. The first category involves charging coordination among EVs at smart parking lots (in commercial, industrial, or residential areas). Hence, coordination takes place among a set of stationary (parked) EVs. In this context, coordination is adopted on a temporal basis. The second category involves charging coordination among mobile EVs that may require fast charging when moving on the road, such as electric buses and taxis. Hence, coordination is implemented on both spatial and temporal basis.

The main challenge when dealing with charging coordination for EVs within parking lots is how to anticipate the future EV charging demand for better temporal coordination. Specifically, in literature, the EV charging coordination decisions take into consideration the current and future regular loads and only the current EV charging demands and how long these EVs are expected to stay in the parking lot. Based on this information, a central vehicle controller (CVC) unit decides which EV to be charged and which to be deferred to a future time slot. However, better coordination can be achieved if the CVC unit has some insights regarding also the future EV charging demands. This approach can be realized via a smart real-time coordination system (SRTC) Shaaban et al. [2014b]. The SRTC enables both charging and discharging of EVs to allow energy exchange among vehicles, and hence, better satisfies the customers requests. It consists of three units. The first is a data collection unit that gathers information about the EV current power demands, the current EV battery SOC, the EV arrival and departure rates over the day within the parking lots (based on historical data), and the current and future regular loads.

The second unit is a prediction unit that forecasts (with a small prediction error probability) the number of EVs that will be simultaneously present in the parking lot during the next time interval, given the gathered information. The last unit is an optimization unit that determines the charging and discharging coordinated decisions based on the current and future (anticipated) power demands of both EVs and regular loads. The coordinated decisions aim to maximize the customers satisfaction while minimizing the system operating costs in terms of cost of power losses and peak demand charges (calculated based on the peak load reached within each time interval). Simulation results shown in Figure 5 for high EV penetration level demonstrate that the SRTCS reduces the EV load during the peak periods of the regular load (i.e., at 3 : 30 and 10 : 30 pm) either using a charging only strategy (SRTCS-C) or by enabling a charging and discharging strategy (SRTCS-C/D). The EV load peak using the SRTCS occurs during the off-peak periods of the regular load. Define the strategy success factor as the average success of EV charging for all EVs in the system over the day. The SRTCS-C and SRTCS-C/D strategies have success factors of 91.3% and 97.7%, respectively. On the other hand, a first-come-first-served (FCFS) strategy has a success factor of 85% and the uncoordinated charging results in infeasible decisions that violate the power grid technical limitations (i.e., cause overload problems).

Mobile EVs, such as electric buses and taxis, may require fast charging while moving on the road. In this context, given a set of EVs and charging stations within a geographical region, it is required to assign EVs to the stations to get charged while avoiding overload problems. Consequently, another dimension is added to the coordination problem, namely, the spatial dimension in addition to the temporal one. Specifically, besides determining the appropriate

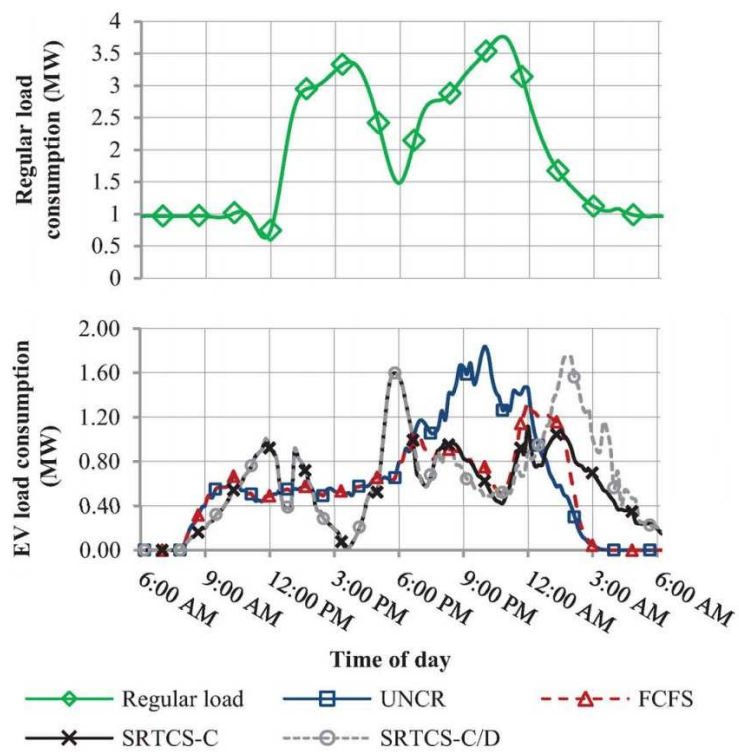


Figure 5: Performance of SRTCS charging and discharging coordination for parked EVs in comparison with uncoordinated charging and first come first served charging coordination Shaaban et al. [2014b].

charging instant for different EVs, it is required to determine the appropriate charging station. This is mainly due to the fact that different charging stations located at different buses experience both temporal and spatial fluctuations in their load capacity Wang et al. [2015]. To enable the spatial and temporal charging coordination strategy, information regarding the fluctuating load capacities at the charging stations should be provided. Furthermore, the designed strategy should account for the EV real-time information such as its location and current SOC. This information is necessary to address the range anxiety problem that represents the tension between the EV travel cost (i.e., consumed energy on the road to reach the charging station) and the EV battery level. Overlooking the range anxiety problem may result in the EV battery being depleted on the way to the assigned charging station. A larger total-EV-charging energy (TECE) can be achieved, as shown in Figure 6, compared with a strategy that adopts only temporal coordination. The TECE gain can reach up to 35%.

The EV charging demand profile is mainly shaped by the customers' preferences, which can be controlled through economic incentives, as in DSM strategies. Consequently, price control can be adopted as an effective tool to align the EV charging demands to the power grid available resources Bayram et al. [2014]. The charging station operator can calculate an optimal arrival rate that results in an acceptable blocking probability for the EV customers' charging requests. The charging station then regulates the charging requests arrivals to comply with the optimal arrival rate value by offering a discount to EV customers in return of postponing their charging requests to the next time interval. The EV customers that refuse to defer their charging requests may be subjected to service blocking. The optimal discount value is calculated such

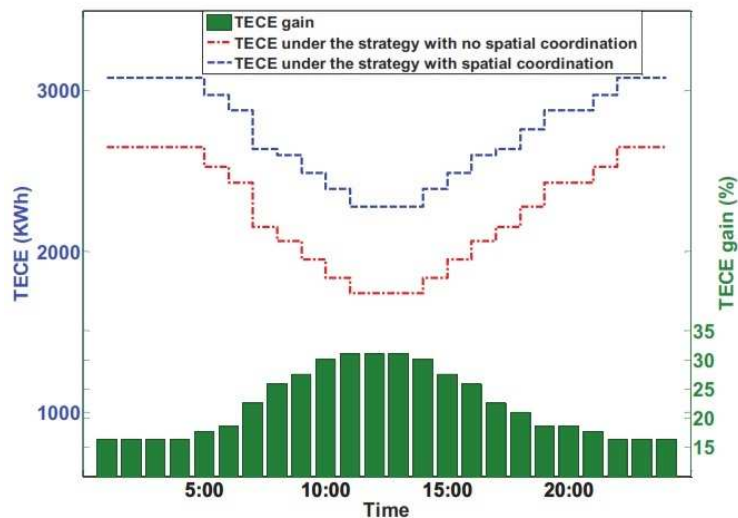


Figure 6: Performance of spatial and temporal charging coordination of mobile EVs in comparison with temporal only coordination Wang et al. [2015].

that it maximizes the charging station profit and satisfies the optimal arrival rate. The EV charging demand profile shaping through this strategy is shown in Figure 7 where the EV's two peak charging demands are offloaded to the next time intervals through incentives. This relieves the stress on the power grid and reduces the blocking probability of the EV charging requests.

Vehicle-to-vehicle (V2V) energy exchange through swapping stations offers an efficient approach to offload the EV high power demands and ensure overload avoidance. In this context, the main challenge for the V2V coordination strategy is twofold: 1) charging coordination for a set of EVs and 2) offering incentives to another set of EVs for discharging. The main objective is to ensure that the demand and supply are matched without requiring any additional (complement) energy from the power grid. Again, price control mechanisms can motivate EVs to contribute to a V2V energy transaction thanks to the expected low cost for charging EVs and high revenue for discharging EVs Wang et al.

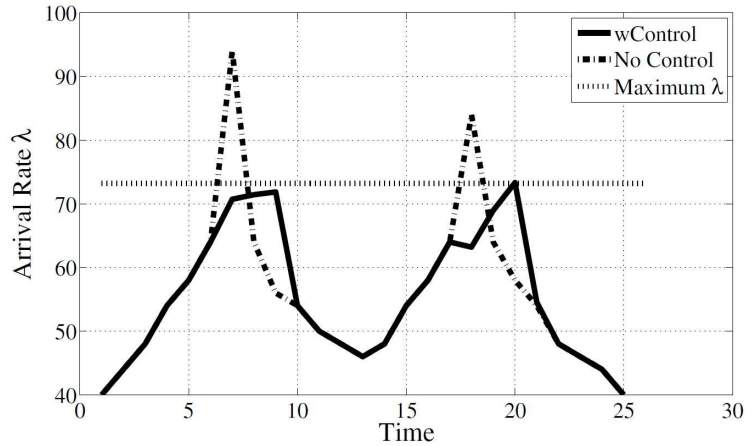


Figure 7: Demand shaping of EVs using price control strategy Bayram et al. [2014].

[2014, 2018].

0.2.2. Communication Requirements for Smart Grid Services

Table 1 presents a summary of the communication requirements of selected smart grid services for the collection of monitoring data, and transmission of pricing data and control signals. The communication requirements are expressed in terms of data size, latency, and reliability. Furthermore, the frequency of transmission is also highlighted. The data in Table 1 is adopted from Kuzlu et al. [2014]. As shown in Table 1, different services present high reliability and low latency requirements. This is especially true for distribution and transmission system monitoring applications such as state estimation and voltage stability monitoring. In addition, transmission of control signals poses high reliability requirements. It should be noted that the amount of data to

Table 1: A summary of communication requirements for different smart grid applications.

		Application	Data Size	Sampling	Latency	Reliability
Monitoring Data Collection	Customer's Consumption	Communication between home appliances and customer's SM/energy management system	10-100 bytes	Once every configurable period (e.g., 15 minutes)	Seconds	> 98%
		On-demand customer's SM reading: from SM to utility	100 bytes	As needed	< 15 secs	> 98%
		Scheduled customer's SM reading: from SMs to AMI head end	1600 – 2400 bytes	4-6 times/day	< 4 hrs	> 98%
		Bulk customer's SM reading: from AMI head end to utility	MB	Multiple times/day for group meters	< 1 hr	> 99.5%
		EV charging status: from EV to utility	100 bytes	2-4 times/day	< 15 secs	> 98%
	Distribution & Txion	Distribution system monitoring: from line meters and field devices to utility	100-1000 bytes	1 time per device per hour	< 5 secs	> 99.5%
		Voltage stability monitoring	> 52 bytes	Once per 0.5 – 5 secs	< 30 secs	> 99.9%
		PMU-based state estimation: from PMUs to utility	> 52 bytes	Once every 10 milli-secs	< 10 milli-secs	> 99.9%
		Dynamic state estimation: from line meters to utility	> 52 bytes	Once every 0.2 - 10 milli-secs	< 10 milli-secs	> 99.9%
	Pricing Data Transmission	TOU: from utility to customer's SMs	100 bytes	1 time/device per price data txion event 4 times/year	< 1 min	> 98%
		CPP: from utility to customer's SMs	100 bytes	1 time/device per price data txion event 2 times/year	< 1 min	> 98%
		RTP: from utility to customer's SMs	100 bytes	1 time/device per price data txion event 6 times/day	< 1 min	> 98%
Pricing to EVs: from utility to EVs		255 bytes	1 time per EV per 2-4 day	< 15 secs	> 98%	
Control Signaling	DLC: from utility to customers	100 bytes	1 time per device per event	< 1 min	> 99.5%	
	ESS Charge/discharge command	25 bytes	2-6 times/ dispatch period /day	< 5 secs	> 99.5%	
	Distribution system demand response	150-250	1 time/device per 12 hrs	< 4 secs	> 99.5%	

be transmitted presents a large volume due to the mass number of involved devices such as SMs, PMUs, EVs, etc.

As discussed in the introduction section, such high reliability and tight latency requirements cannot be satisfied by 4G networks. For instance, the state estimation application requirement of 10 milli-seconds latency with 99.9% reliability requirements cannot be achieved when 4G networks are employed. Another major concern is how to guarantee that the requirements of these applications are simultaneously satisfied. On the other hand, 5G networks can address these limitations through a set of unique features such as massive connections, ubiquitous connectivity, ultra-low latency, ultra-high reliability, and very high throughput. These features can be achieved in 5G networks thanks to a group of novel concepts, namely, network slicing, NFV, SDN, and cloud computing. In the following, we briefly introduce these concepts for the sake of completeness, while more detailed information can be found in the introductory chapter of the book.

5G Fundamental Concepts

Network Slicing The concept of network slicing enables the network operator to slice (split) one physical network into multiple virtual networks, where each virtual network is optimized for a specific service. A key concept in network slicing is physical resource isolation, where the physical resources allocated to one network slice cannot be shared by other slices. Hence, multi-tenants co-exist on the same physical network in logical isolation. Cloud computing, NFV, and SDN are key enabling technologies to implement vertical slicing of the core, transport, and radio access networks and horizontal slicing of the terminals A2 [2017].

Cloud Computing mobile cloud computing (MCC) was introduced to act

as an infrastructure as a service (IaaS) for data processing and storage outside the mobile device. This approach can also be regarded as an offloading technique of computation-intensive tasks from a resource-constrained device to a resource-sufficient cloud environment Taleb et al. [2017]. In terms of network slices, this is viewed as a horizontal slicing approach that helps devices to go beyond their physical limitations via resource sharing among high capable network nodes and less capable devices A2 [2017]. Unfortunately, MCC services offered through public clouds suffered from long response times, and hence, failed to fulfill the latency requirements due to the centralized cloud architecture model. In turn, this affected the users' quality-of-service (QoS). To address such a limitation, the concept of edge cloud was introduced through Fog and Mobile Edge Computing.

Network Function Virtualization The idea behind NFV is to decouple the network functions and services from the hardware devices. As a result, network functions and services such as packet data network, serving gateways, firewalls, and load balancing can be implemented in software. One advantage of NFV is that network functions and services can be uploaded into cloud platforms, which enables savings in both capital and operational expenditures. Furthermore, NFV allows a high flexibility both in data and control planes, where any required upgrades and resource scaling can be implemented in software. The concept of NFV is a key enabler to vertical slicing of the core network A2 [2017]. In specific, NFV enables the co-existence of multi-tenants on the same physical hardware and splits the load balancing function from the hardware.

Software Defined Network The goal of SDN is to transform the decentralized network architecture into a centralized one by separating the packet

forwarding process (data plane) from the routing decision making process (control plane). Such a decoupling makes the network switches become simple forwarding devices while the routing control actions are taken by a centralized controller that instructs the physical devices. This enables the network control to become directly programmable. As a result, the underlying network infrastructure can be abstracted from the network services. The SDN architecture consists of the following layers Chen et al. [2017]: 1) Application layer, which presents a set of programs that communicate their desirable network requirements and behavior to the SDN controller via a northbound interface (NBI), 2) control layer, which assigns instructions to the hardware devices (routers and switches) via a southbound interface (SBI) in accordance to the application layer requirements, and 3) physical layer, which consists of a set of hardware devices that follow the control layer instructions to accomplish the data transfer task. The concept of SDN is a key enabler to vertical slicing of the transport network A2 [2017]. In specific, transport network slicing consists of slicing of both the control and forwarding planes. The control plane provides the necessary resource allocation for the forwarding plane, while the forwarding plane provides the QoS guarantee given the requirements of different network slices.

The above discussion illustrates that both SDN and NFV rely on virtualization to abstract the network infrastructures in software, which then will be implemented across the hardware platforms. In summary, SDN aims to separate the network control functions from the forwarding functions, while NFV abstracts network forwarding and other network functions from the hardware devices on which they run. Both concepts are useful to implement virtual networks that can share the same substrate network and operate independently and in isolation Lv et al. [2014]. This is also known as external network virtu-

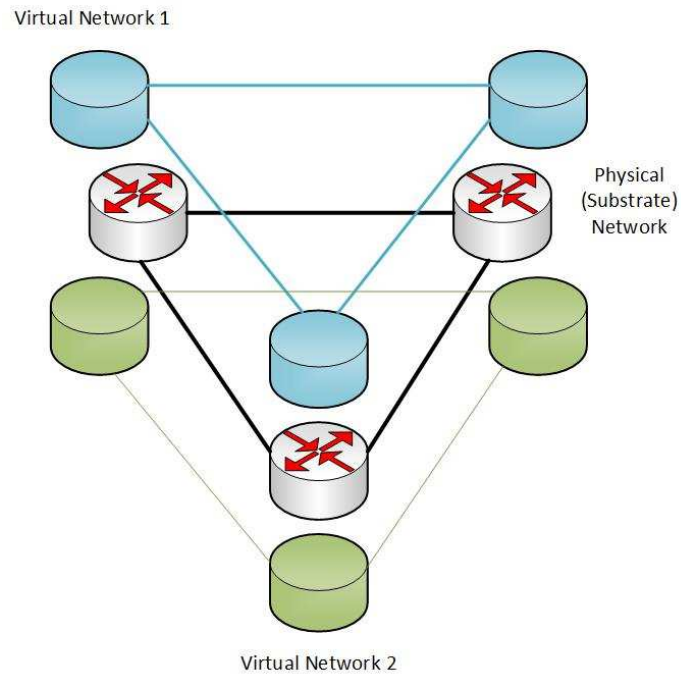


Figure 8: Illustration of the network virtualization concept.

alization, which splits one or more networks into a set of virtual networks. As shown in Figure 8, each substrate node can support a set of virtual nodes that will operate without interfering with each other.

0.3. Smart Grid Services Supported by 5G Networks

This section demonstrates how the 5G new concepts such as SDN, network virtualization, and cloud computing offer enhanced services for grid monitoring, data processing, DSM, and EV charging and discharging coordination. A summary of the application of these concepts in supporting the smart grid

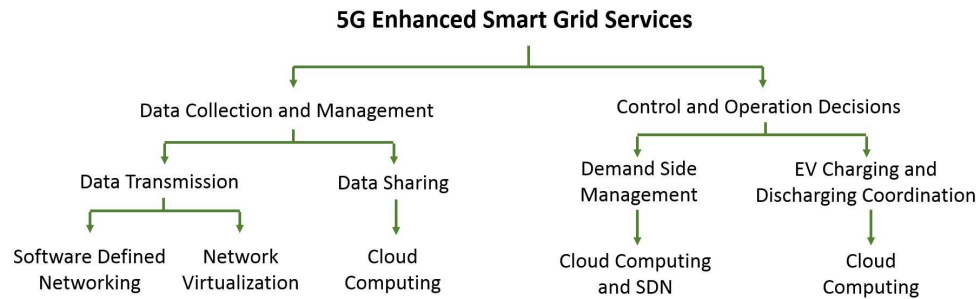


Figure 9: Summary of the application of 5G concepts in supporting smart grid services.

services is illustrated in Figure 9.

0.3.1. Data Collection and Management Services

This subsection is divided into two parts. The first part illustrates how to efficiently transmit the readings of SMs, PMUs, and sensors using concepts of SDN and network virtualization. The second part explains how to use cloud computing to share these readings among different operators, and hence, achieves a more accurate grid monitoring service, while detecting any malicious readings.

0.3.1.1. Data Collection Services

SDN-based Solutions As illustrated in Section 2, the future smart grid is characterized by massive number of SMs, PMUs, sensors, and actuators that are allocated at DG and ESS units, transmission and distribution lines, and inside the smart homes. In addition, some of the meters' sampling frequency is expected to be quite high (e.g., for PMUs as shown in Table 1). As a result, a huge volume of data will be generated at the future smart grid that needs to be

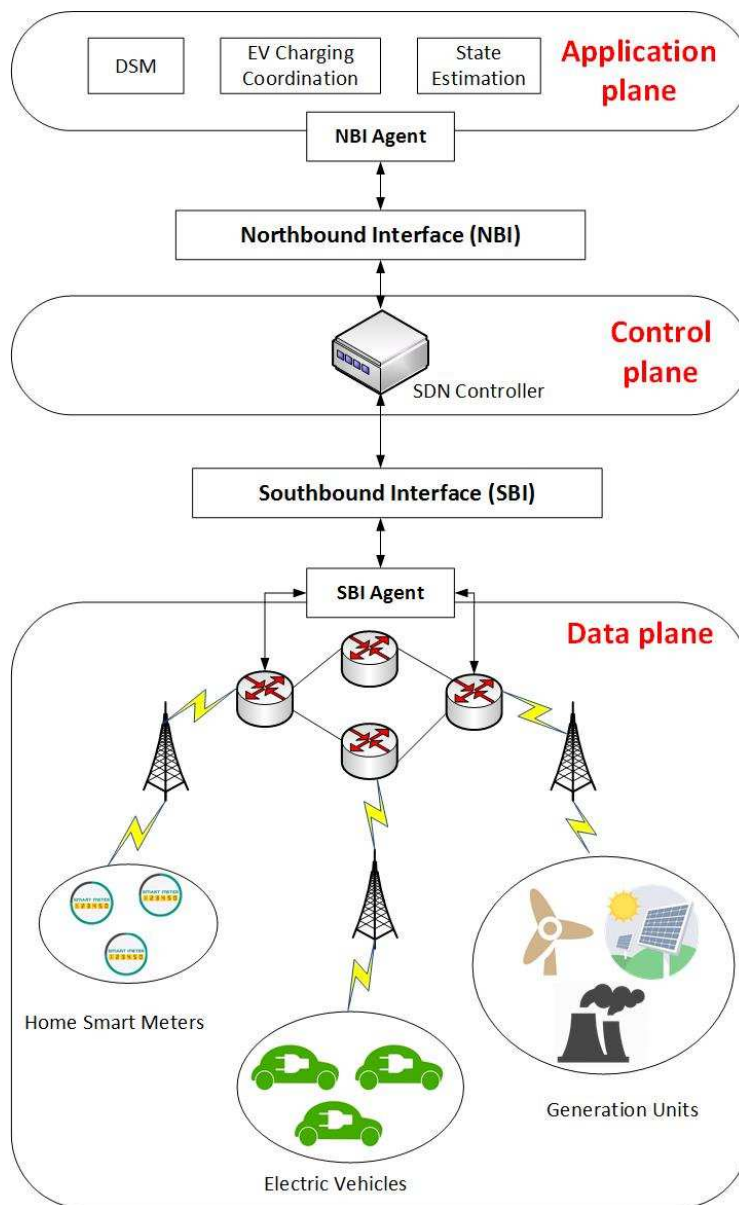


Figure 10: Illustration of SDN application in smart grid data collection.

efficiently routed in real-time among various geo-separated entities. This poses some challenges related to managing the communication network resources. A traditional static communication network presents an inefficient solution to handle the real-time data acquisition process in the smart grid due to the expected high delay, poor bandwidth utilization, inefficient routing, and low throughput. To ensure a reliable data flow in real-time over the underlying communication network, SDN presents an effective solution due to its flexibility, programmability, and self-configuration. As the routing decision making is taken at a central controller in the SDN paradigm, fast data forwarding can be done in real-time Chaudhary et al. [2018]. Figure 10 illustrates the application of SDN in supporting the smart grid data collection service. Thanks to the centralized control mechanism in SDN, optimal routing paths that ensure target QoS can be established. Furthermore, efficient management of the network resources can be achieved by direct programmability and effective cross-layer design. Moreover, centralized control of the communication network via SDN offers enhanced capabilities against cyber-attacks by fast isolation of the compromised communication devices, efficient dropping of malicious traffic, and establishing on-demand paths in response to a cyber-attack Jin et al. [2017].

In literature, two schemes are deployed to handle the smart grid big data in real-time via SDN. The first approach integrates SDN with data dimensionality reduction techniques Kaur et al. [2018]. In the data plane, data is acquired from the SMs, PMUs, and sensors. The Frobenius norm is firstly applied to the collected data to generate reduced tensors with minimal reconstruction error for efficient data representation. By representing the smart grid big data using tensors, redundant and ambiguous dimensions can be removed, which enables a reduced transmission time. For instance, if a data frame with a size of 20

Mbits is transmitted at a data rate of 20 Mbps, it will reach the destination node in 1 second. Now, by reducing the data frame size to 16 Mbits and transmitting it with the same data rate, the transmission time will be reduced to 0.8 seconds. Upon decomposing the collected data into tensors of reduced size, the SDN controller (in the control plane) will dynamically determine the optimal routing paths that can achieve low latencies and high QoS. These routing decisions will be sent from the SDN control plane to the SDN data plane via the SBI, and hence, the forwarding nodes at the data plane implement such routing decisions. A routing algorithm is presented in Kaur et al. [2018] for the SDN controller using an empirical probability-based scheme that estimates the paths to forward the reduced data. The results in Kaur et al. [2018] show that the estimated path offers low latency and high throughput. Furthermore, the routing scheme in Kaur et al. [2018] is shown to achieve high route estimation accuracy even with increased packet losses. Moreover, the routing scheme in Kaur et al. [2018] achieves high bandwidth utilization and avoids any under-utilization of bandwidth or network congestion. Another routing algorithm is proposed in Montazerolghaem et al. [2018] based on an integer linear programming model, which is an NP-hard problem. Given a set of SMs, MDMSs, and switches, the objective is to route the generated data from the SMs to the appropriate MDMS via the switches. To address the associated computational complexity, the original problem is decomposed into two sub-problems, where the first sub-problem deals with the selection of the appropriate MDMS while the second sub-problem find the optimal path to reach the selected MDMS. The second approach that is adopted to handle the smart grid big data in real-time based on SDN follows a hierarchical framework Chen et al. [2017]. Generally, the distribution network of the power grid has two tiers, where the

first tier carries the power from the substation to the primary feeders and the second tier carries the power from the primary feeders to the secondary feeders to supply the residential units. Hence, to achieve a good management of resources, the SDN-based hierarchical framework of Chen et al. [2017] implements two-tiers as well. The SDN controller of the first tier is deployed at the substation, which aims to present a wide view of the system. This controller is responsible for routing the data from the SM aggregators to the substation at the primary network. The SDN controller of the second tier is implemented at the aggregator itself and aims to manage data collection from the SMs to reach the aggregator at the secondary network. Such a hierarchical implementation offers a flexible and efficient way to manage big data collection in the smart grid while offering global monitoring of the power grid.

It is shown in Montazerolghaem et al. [2018] that NFV can work with SDN to efficiently overcome any constraints in resources while processing the smart grid big data in the MDMSs. Specifically, the networking resources such as switches and routers will be managed the SDN controller while all other resources required for processing and storing the data will be managed by the NFV orchestration. In this context, virtual MDMSs will be created and a set of hypervisors will manage the resource split among these virtual MDMS and the SDN controller will determine the forwarding tables for all switches such that the SM data can be efficiently routed to the appropriate virtual MDMS. Such an integration between SDN and NFV offers a customizable and programmable virtualized MDMS that can be efficiently scaled according to the incoming SM traffic load.

Network Virtualization-based Solutions Different types of communication networks can be employed for data transmission in the distribution

grid such as wireless mesh network (WMN), power line communication (PLC), cellular networks, and vehicular ad-hoc networks (VANETs). However, these networks may suffer from packet loss and bit-error-rate due to interference and attenuation. Hence, a single network cannot guarantee real-time service support with low latency and high reliability as required for smart grid applications. Using network virtualization, it is possible to integrate different heterogeneous networks for efficient data collection with high QoS guarantee. For instance, in Lv et al. [2014], smart grid real-time services are supported by virtual networks that are mapped to WMN and PLC. Through virtual network embedding, virtual nodes and links are mapped onto the substrate nodes and paths. To achieve the high-reliability requirement, real-time services were supported in Lv et al. [2014] by virtual networks that are mapped to both WMN and PLC via concurrent transmission, multiple subcarrier allocation, and time diversity. On the other hand, a single network mapping is adopted in Wang et al. [2018] to support data collection from mobile EVs regarding the battery SOC, power charging demands, and EV current location. In this framework, the EV first uses the VANET for data transmission when the connection probability is estimated to be larger than a predefined threshold, e.g., 80%. When the connection probability in the VANET is below this threshold, the EV employs the cellular network to transmit the real-time data. Such a variation in the VANET connection probability can be due to a change in the vehicle density or a change in the transmission range. Hence, the network integration solution proposed in Wang et al. [2018] makes use of the VANET low transmission cost and relies on the cellular network only when poor connections are expected in the VANET, in order to guarantee successful information transmission. Furthermore, such an approach helps in relieving possible con-

gestions induced by EV transmissions over the cellular network.

Cloud Computing-based Solutions Data transmission in smart grids are mostly carried out in a hierarchical architecture, where data is first transmitted from SMs to aggregators and then aggregators forward this data to the smart grid control center. One way to efficiently implement this aggregation is based on Fog cloud nodes. In this paradigm, the grid is divided into a set of regions/microgrids and a Fog node is assigned to each microgrid. Data is transmitted from the SMs in each microgrid to the Fog node in charge of this microgrid. Each Fog node will implement in-network aggregation and then forward this data to the smart grid control center, which could be implemented in the core cloud. However, a serious concern that is raised in this context is related to preserving the privacy of the customer's data. In order to minimize the privacy leakage, Gaussian noise addition is employed at the Fog nodes to present a differential privacy guarantee Lyu et al. [2018]. This technique of noise addition has also been investigated in Sherif et al. [2018], and the results indicate that such an approach improves the data anonymity and presents a minimal impact on the optimality of the decisions to be taken using the noisy measurements. Furthermore, to ensure the aggregator obliviousness, data encryption is adopted in Lyu et al. [2018] and both encryption and permutation techniques are adopted in Sherif et al. [2018].

0.3.1.2. Data Management Services

Cloud Computing-based Solutions In a liberated electricity market, the power grid is divided into regions and each region is monitored and managed by an independent system operator (ISO) or a regional transmission organization (RTO) that coordinates the transmission utility companies to ensure

reliable, efficient, and secure regional power system. Each ISO manages a set of PMUs and sensors that are used to monitor its region of the grid and implements a separate state estimation to observe the voltages at different nodes and ensure they do not violate the minimum and maximum thresholds. However, to enable coordination among such ISOs, wide area monitoring is required. As a result, data sharing among ISOs should be carried out in a secure, scalable, and cost-effective way with low latency for real-time service support. An open source cloud computing platform, namely GridCloud, is proposed in Anderson et al. [2018] to implement such a data sharing objective in the most efficient manner. Data from PMUs, SMs, and sensors of different ISOs and utility companies flow into a shared cloud-computing platform for storage and processing. State estimation task can be carried out using the shared data from all collaborating entities to present a wide visualization of the system state, and hence, better coordination can be achieved among different regions. ISOs and utility companies can draw the shared data and analytic outputs to better manage their assets. The GridCloud platform offers several advantages such as consistent data availability at a massive scale. High availability is achieved at GridCloud as data is saved redundantly over multiple servers. Furthermore, redundant connections are also established to ensure reliability in response to communication link failures.

In addition to supporting data sharing services, cloud computing presents an effective tool to mitigate cyber-security attacks. Since a massive number of SMs will be deployed in the customers' premises, these meters are considered to be unprotected devices that are distributed in the low-trust environment. Being the primary access to the AMI network, such SMs pose serious security threats. Specifically, any manipulation of the data transmitted through these

SMs directly impact many services in the smart grid such as consumption monitoring, DSM, and billing. In this context, cloud computing can provide cyber-security solutions via a security-as-a-service (SECaaS) model. The work in Hasan and Mouftah [2018] proposes a cloud-centric collaborative monitoring architecture that involves two major participants. The first participant is the smart grid operator that owns an AMI network to collect data from the SMs for monitoring and DSM purposes and the second participant is a SECaaS provider that offers network security monitoring, encryption key management, and security assessment. At the smart grid operator side, monitoring and decision entities are established to perform initial screening of data for assessment against security attacks, such as data manipulation attacks, based on a set of predefined criteria. After this initial screening, data is transferred to a cloud computing platform that consists of a set of powerful servers that will run advanced analytical tools, e.g., deep machine learning techniques. For instance, a deep feed-forward neural network is designed in Ismail et al. [2018] to efficiently detect data manipulation attacks in AMI networks. Detection latency represents a very important performance evaluation metric. This latency is translated to a time difference between detecting a cyber-attack event and taking the appropriate response. In order to minimize the overall detection latency, a placement problem is formulated in Hasan and Mouftah [2018] to find the optimal location for the cloud servers in order to minimize the access link latency, and hence, the overall latency.

0.3.2. Operation Decision-Making Services

This subsection is also divided into two parts. The first part explains how to employ the concepts of cloud computing and SDN in supporting decision making for DSM. The second part focuses on employing these concepts in supporting decision making for EV charging coordination.

0.3.2.1. Demand Side Management Services

Cloud Computing-based Solutions Usually, DSM programs run in a distributed fashion via iterative algorithms. Customers are assumed to belong to different clusters (microgrids). Each customer within a specific microgrid solves locally an optimization problem and then broadcasts some information update to other customers in the microgrid to update global parameters for this microgrid. This procedure is repeated until all customers converge to the global optimal decision, which can be in form of appliance scheduling decisions. There are several implications with this approach. First, decisions about dynamic pricing and coordination among different microgrids need to be taken in real-time. When the communication channel among the customers is not ideal, the update messages that are exchanged among the customers might be lost. Using transmission control protocol (TCP) in transferring the update messages will increase the convergence time to reach the global optimal solution, as the same update message will be re-transmitted several times until an acknowledgment message is received from all customers. On the other hand, by adopting a user datagram protocol (UDP), the delivery of the update messages is not guaranteed. As a result, the DSM optimization problem might converge to a non-optimal solution as outdated update messages will be used at some customers. Second, high computational power is required to solve the DSM op-

timization problem in a reduced time. The local problems to be solved at each customer will be handled by the customer's home energy management system (HEMS) or smart meter, which does not present the required computational, memory, and storage capabilities to tackle such optimization problems. Cloud computing-based solutions offer a semi-centralized mechanism that can effectively address the aforementioned challenges. These solutions assume a two-tier cloud computing architecture consisting of an edge cloud (or a Fog cloud) and a core cloud Yaghmaee et al. [2017, 2018], Yaghmaee and Leon-Garcia [2018]. Customers within each microgrid are controlled by an edge (Fog) cloud to provide the required computational and storage resources that can meet the desirable low latency. The core cloud solves a centralized optimization problem to coordinate the operation of different microgrids. Energy consumption data, local generation from DG units, and available energy at ESS units are transmitted from the customers to the edge cloud, which solves an optimization problem to determine the optimal power consumption schedule for the customers' appliances and ESS units. Each edge cloud then forwards the total load at each microgrid to the core cloud, which will solve a centralized problem to coordinate the resource usage among the microgrids in order to minimize the overall cost. Figure 11 illustrates the two-tier cloud-based solution for DSM. This two-tier cloud-based solution presents several advantages as follows: 1) The semi-centralized approach alleviates the challenges related to the wireless channel quality, in terms of packet loss. The customers only forward their data to the edge cloud and the edge cloud is responsible for solving the scheduling optimization problem, and hence, issues related to missing or outdated update messages due to a poor channel quality is no longer a concern. 2) The two-tier approach offers the high computational power that is required to solve the DSM

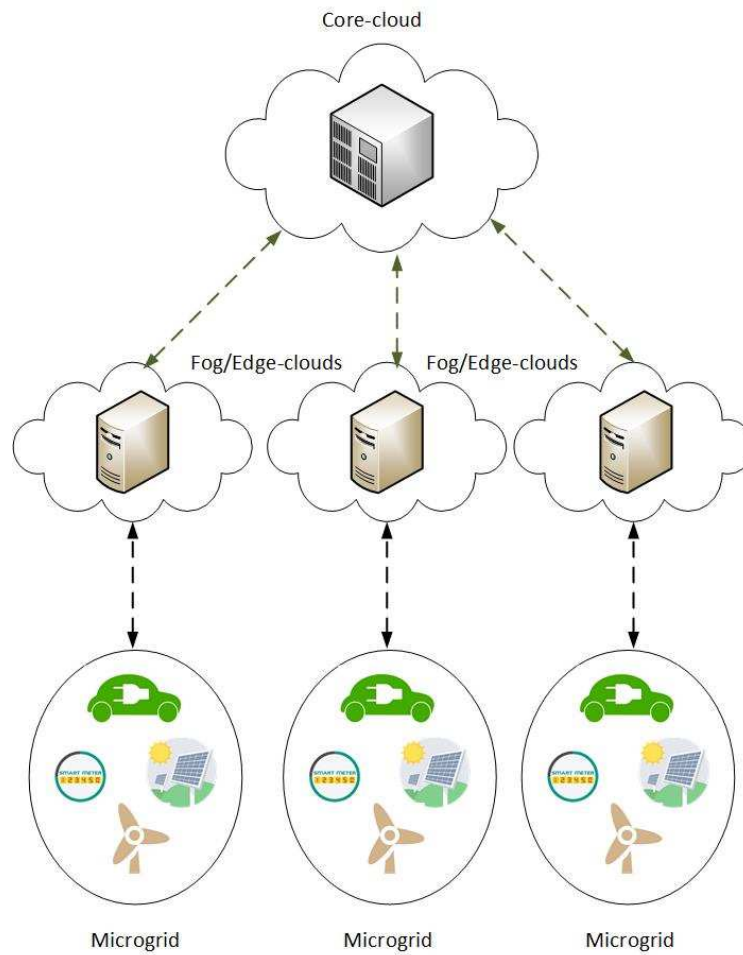


Figure 11: Illustration of the two-tier cloud-based DSM solution.

optimization problems since all the calculations are done at the edge and core clouds without any computational burden on the HEMS or SM at the customer premises. 3) This approach also provides the necessary storage capabilities at the cloud servers and reduce the volume of traffic that is required to traverse the communication network backbone. 4) A major advantage provided by the cloud-based solutions is that they can leverage the cloud defense mechanisms against privacy and security cyber-attacks, unlike the traditional peer-to-peer distributed DSM solutions that are vulnerable to cyber-security attacks and also may violate the customers' privacy.

The concept of SDN can be well integrated with cloud computing to offer a flexible and scalable DSM service in smart grid Chekired et al. [2018]. In this context, all communication networks that are responsible for collecting the meter readings are managed and controlled via SDN to ensure real-time information delivery for decision making, while the cloud data servers handle the DSM decision making process. The SDN controller can be implemented inside the cloud to manage the backhaul network. The SDN controller supervises the communications between the microgrids and the edge (Fog) cloud. It is shown in Chekired et al. [2018] that when the power consumption requests increase in the grid, the Fog-SDN mechanism results in a reduced response time compared with a centralized core network infrastructure. This is due to the fast access provided by the distributed Fog nodes and the fast data forwarding actions carried out by the SDN.

0.3.2.2. Electric Vehicle Charging and Discharging Services

Cloud Computing-based Solutions Charging and discharging coordination can be implemented in a distributed manner where several EVs engage in an iterative algorithm to reach global scheduling decisions Wang et al. [2018]. However, these EVs might not have the computational power, memory, and storage capabilities that are required to participate in solving such a large scale optimization problem. Solving these coordination problems in a centralized manner might not also be efficient, as high latency could be incurred when solving the coordination problem by a control unit that is located farway from moving EVs. One solution to address this problem is achieved by using mobile edge computing to offload the complex computations to be processed at the network edge, which as well reduces the associated latency. A four-layer framework is proposed in Kumar et al. [2016] to coordinate charging and discharging requests of EVs in an efficient manner. The lowest layer includes the EVs and the second layer consists of routers and gateways deployed in the network backbone. The third layer includes a set of servers that are distributed at different geographical locations at the edge of the network, and the top-most layer represents the core-cloud infrastructure. The charging and discharging requests will be routed from the EVs at the first layer by the routers and gateways in the second layer to reach the nearest data server at the network edge to determine the optimal decision. Coordination among different data servers is implemented at the core-cloud to specify real-time pricing information from the owner of the charging station to the EVs.

The framework in Kumar et al. [2016] does not take into consideration service differentiation between moving and parked EVs. While moving EVs must

be served in real-time, parked EVs can tolerate longer delays. The framework presented in Kong et al. [2018] accounts for this fact and presents a hierarchical cloud-based EV charging coordination model that involves two levels of cloud computing infrastructures that can meet different latency requirements of different customers. In specific, two types of clouds are defined. The first type is referred to as local cloud, which presents shorter end-to-end delay, while the second type is a remote cloud that presents a relatively longer end-to-end delay. Two classes of services are considered, namely, high priority (HP) and low priority (LP) charging service. Mobile EVs are offered high priority service as they require real-time service, while parked EVs are offered low priority service as they have comparably longer latency requirement. The EVs in HP and LP services communicate with the local and remote clouds, respectively. The remote cloud aims to collect the information from the EVs in parking lots and synchronize the data with the local cloud to reach optimal charging coordination decisions.

0.4. Summary and Future Research

In this chapter, the application of 5G novel concepts in supporting advanced smart grid services is discussed. Concepts of SDN and NFV find great application in data collection from the massive number of SMs, PMUs, and sensors that are deployed across the smart grid. Through these two concepts, flexible and dynamic routing of big volume of data among various geo-separated locations can be achieved in real-time. Furthermore, the concept of cloud-computing, especially Fog and mobile edge clouds, find great application in data management and decision making in smart grids. In specific, efficient and

secure sharing of sensor data is possible among various ISOs via the cloud, which enables enhanced monitoring services for the grid, and hence, more informative decisions can be taken. In addition, cloud-computing is very useful in offloading the complex computations that are needed in order to reach optimal scheduling and coordination decisions in real-time for DSM and EV charging and discharging.

The research work in supporting smart grid services via 5G network concepts is still in the early stage and further investigations are required to several open challenges, as follows:

- The existing research works mainly focus on smart services that are still considered to be relatively delay tolerant if compared with other emergency services. For instance, the self-healing capability of the smart grid requires fast detection, localization, and isolation of faults within the grid while ensuring continuity of power flow. This kind of emergency services poses more stringent latency requirement than DSM and EV charging and discharging coordination decisions. Further attention should be given to design effective communication platforms based on the novel 5G concepts to support the tight delay constraints of emergency services.
- The existing research focuses mainly on a single application scenario in smart grid and design the communication network based on the requirement of this application. However, the developed frameworks are not investigated when competition on resources exists among different applications. For instance, how can we dynamically schedule the network resources among different slices, each supporting a specific smart grid service, e.g., data collection, DSM operation, and EV charging and discharging coordination, while satisfying their QoS requirements? Static allocation of resources among these

services might result in over or under provision situations, which either lead to inefficient utilization of the available resources in case of over provision or negatively affect the smart grid services in case of under provision. More importantly, how can we schedule the network resources among slices of different industries, e.g., smart grid, health care services, etc? How can we guarantee that these services meet their QoS requirements and ensure proper isolation among them, especially in a peak load network condition? Hence, the investigation of the developed communication platforms for smart grid services need to be investigated in a more realistic network setting that involves supporting different industries at peak network conditions.

- Further investigations are required on the application of machine learning-based techniques for network management. For instance, dynamic routing in SDN controllers can be designed using advanced machine learning tools, which enables more intelligent routing mechanisms that can easily and quickly adapt to the network conditions and the smart grid service requirement. Moreover, the management of virtual network resources can be carried out more efficiently using machine learning-based tools.
- Future research should focus on finding robust solutions to the challenging security threats that face the future 5G networks, which hinder their application in supporting the communication requirements of critical infrastructures such as the smart grid. Attackers may exploit the capacity elasticity of one network slice to consume the network resources that may be used to support smart grid services. Furthermore, effective security measures must be ensured while performing power grid applications on the cloud. Moreover, the existence of a single SDN controller may represent a security challenge for the data routing services within the smart grid, as it represents a single

point of failure that may jeopardize the data collection service within the smart grid if the SDN controller was subject to a security attack.

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