DYNAMIC ENERGY DISTRIBUTION IN SMART GRIDS ENABLED BY INTERNET OF THINGS SENSORS AND HYBRID TELECOM NETWORKS

by

Ravil Bikmetov

A dissertation submitted to the faculty of
The University of North Carolina at Charlotte
in partial fulfillment of the requirements
for the degree of Doctor of Philosophy in
Optical Science and Engineering

Charlotte

2019

Approved by:

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Dr. Yasin Raja

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Dr. Khurram Kazi

____

Dr. Churlzu Lim

____

Dr. Michael Fiddy

____

Dr. Badrul Chowdhury

____

Dr. Mirsad Hadzikadic

ABSTRACT

RAVIL BIKMETOV. Dynamic Energy Distribution in Smart Grids Enabled by Internet of Things Sensors and Hybrid Telecom Networks. (Under the direction of DR. YASIN RAJA)

Ability to manage energy consumption and generation is a major feature of the developed smart grid (SG) paradigm. Implementation of machine-to-machine (M2M) communications supported by hybrid telecom networks and Internet of Things (IoT) sensors plays an important role in dynamic energy management in SGs. As an innovative application of demand energy management, a resilient and secure layered architecture of automated charging station for unsupervised electric vehicles have been proposed. To demonstrate the feasibility of the architecture, an analytical framework has been developed using a bottom-up approach. The main goal of charging station's operation is to optimize scheduling of electric vehicles for their charging service considering an efficient energy distribution. A divide-and-conquer strategy is employed for such scheduling optimization at the operational level real-time decision-making. A mixed-integer linear programming model is considered to solve this online optimal scheduling procedure. A mathematical model and corresponding simulation platform have been developed to perform a further analysis of charging station's operation at various levels of decision-making hierarchy. An illustrative example of the scheduling solution and the developed simulation have been obtained by a Matlab code combined with the Gurobi optimization solver. Operation of the proposed autonomous charging station has been demonstrated based on different decisions on the number of sharable pumps in its tiers. In the demonstrated example the optimization of charging station's operation can be performed by development of rules for dynamic pump sharing and profit-pricing models. As a part of SG, the proposed architecture of charging station relies on available dynamic load scheduling techniques and utilizes M2M communications supported by existing hybrid telecom network infrastructure.

ACKNOWLEDGMENTS

I would like to express my sincere gratitude to my PhD advisors, Dr. Yasin Raja and Dr. Khurram Kazi for advising and mentoring me during past five years. I am thankful to Dr. Raja for his overall advising and introducing me to Dr. Kazi who became my unofficial advisor and mentor as well as my research dissertation committee member the most actively involved in my research. I would like to thank Dr. Raja and Dr. Kazi for exposing me to a new area of my research in the field of distributed intelligence and analytics of Smart Grids. I am very grateful to Dr. Kazi for his enthusiastic and energetic industrial approach in research, which has led to many insightful discussions and innovative ideas such the development of automated charging station, dynamic energy distribution, machine-to-machine communications, etc. I appreciate his diligent, detail-oriented and perceptive problem-solving approach. It was a great practice to learn from a committee member with an extensive industrial experience!

Dr. Lim was the other committee member who has made the most significant contribution in several components of my research at its final and the most important phase. Using his strong background and research expertise, Dr. Lim introduced me to me to the details of a mixed-integer programming modeling, which I have successfully utilized in a discrete event simulation approach and implemented in my developed analytical platform. I am very grateful to Dr. Lim for his systematic advice, which significantly accelerated my dissertation completion, and invaluable suggestions in the parts of my dissertation work related to queueing, scheduling, and optimization. In my opinion, Dr. Lim’s suggestions have significantly improved the quality of my dissertation.

I would like to thank my other committee members: Dr. Fiddy, Dr. Chowdhury, and Dr. Hadzikadic for their service. I am grateful to Dr. Fiddy for his professional revision of my dissertation work and his valuable comments and suggestions that helped to improve its quality. I am thankful to Dr. Chowdhury for sharing his expertise in energy distribution control and automation and specialized suggestions for my final dissertation draft. I am grateful to Dr. Hadzikadic for bringing his expertise in data analytics and helping me to refine the scope and contents of my dissertation.

I would like to express my sincere gratitude to Dr. Boreman, the Chair of the Department of Physics and Optical Science of the UNC Charlotte, for his invaluable support and mentoring in ones of the most difficult questions of my dissertation work such as awards' nominations, conference travel support, etc. With a kind help of Dr. Boreman and my academic advisor, I have been nominated and recognized with Giles Graduate Fellowship award, which significantly accelerated my dissertation progress. In addition, Dr. Boreman has been very helpful with organizing of resolution of various technical difficulties with software during my research work.

I am thankful to the Graduate School of the UNC Charlotte for offering fellowship awards for its graduate students. I was honored to receive one of such awards, Giles Graduate Fellowship, in 2018 – 2019 academic year. Being offered for last year students' dissertation completion, this award played a key role in the successful completion of my research work and my timely defense of my dissertation. Since my research has not been funded, the reception of this award was critically important for me as it provided a remarkable help in dedicating all my available time and efforts to my research. Specifically, I am truly thankful to Julie Goodliffe and Julie Green for their assistance with Giles

Graduate Fellowship application. Julie Goodliffe kindly introduced this award to me and encouraged to apply for it in a timely manner. Julie Green helped me with its requirements clarification and guided me from the beginning of my application to its final submission. In addition, I am thankful to the Department of Physics and Optical Science and its Lab Coordinator, Shree Bhattarai, that provided me with graduate teaching assistantships for 5 years of my PhD enrollment helping me to mitigate the absence of research funding including summer semesters.

I would like to express my gratitude to the UNC Charlotte students who timely helped me with several aspects of my work. Specifically, I would like to recognize Tanmay Sane and Elisa Hurwitz. Tanmay was extremely helpful with overall code organization and testing when dynamic load scheduling technique has been implemented in MATLAB environment. Elisa was exceptionally helpful with revising and proof-reading of my papers and dissertation work. In addition, as a good friend of mine, Elisa was always ready to help with multiple aspects of my preparation, such as practicing of my defense presentation, arranging of pizza and drinks for my defense, etc. I would also like to recognize Natalya Shevchenko, a student of Plekhanov Russian University of Economics, for her professional help with statistical analysis of energy pricing data and insights for my energy pricing model development. Finally, I would like to thank Navid Farahi, Jack Chang, Babar Hussain, Bin Zhang, Yuanye Liu and all students of Optical Science and Engineering, Electrical Engineering, and Computer Science programs who was close to me providing advice and suggestions during my “PhD journey”.

My family members have been the most important to me in the off-work time of my “PhD journey”. I am thankful to my parents for their support and help. I am sincerely grateful to my lovely wife who has been always beside me ready to help with anything she can at the most critical times of my PhD work. She took ultimate responsibility for all home duties and made my rest and recovery from “PhD pressure” as enjoyable as it can be. Thank you very much! I truly appreciate all your help!

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CHAPTER 1: INTRODUCTION

Smart grid (SG) paradigm modernizes traditional energy grids with self-healing, automation, remote control, and ability to manage energy consumption and generation for its efficient operation [1-3]. A vital role in management of energy consumption and generation belongs to an efficient energy distribution, which was addressed by development of various concepts, techniques, and algorithms [4-8]. Dynamic energy distribution is one of such techniques experiencing an ongoing development [9-15]. This technique belongs to the demand side management and implemented using a bidirectional data flow between the energy generation site, energy service providers, and energy consumers located at the energy user site. Dynamic load scheduling is one of the most popular examples of dynamic energy distribution technique, supported by information transfer between energy loads, such as household appliances, industrial machines and equipment, etc., and energy service providers . Such information transfer satisfying the requirements for quality of service (QoS), interoperability, scalability, security and privacy is commonly performed between IoT sensors integrated in energy loads or externally connected to them at the energy consumption site and energy distribution control center located at the energy service provider site [11, 13, 15-22]. Hence, the corresponding telecommunication infrastructure with possible broadband and long distance transmission capabilities is an essential part of energy distribution implementation schemes in SGs.

Electric vehicles (EVs) are another important types of energy loads, which optimized charging is extremely important for an efficient energy distribution in SGs [6, 23-28]. In addition to that, the high level of dynamism of “EV loads” have been announced in the previous studies [23-27]. Advancements in diverse technologies have propelled the growth, development, and deployment of unsupervised Autonomous Vehicles (AVs). Long-batteries with active energy management and quick charging capabilities are making the AVs suitable for everyday use. Intelligent, sophisticated sensor technologies such as 3D imaging, radars, LIDAR, ultrasonic sonars, laser scanners, and GPS are vital to the AV's situational awareness. Highly integrated processors and application specific electronics, very large-scale integrated circuits, navigation and guidance systems, robust and secure software are paving the way for the vehicle's full autonomy. Hence, the need in automated charging stations for autonomous electric vehicles (AEVs) is foreseen in the nearest future [29-32]. To assure an optimized scheduling of incoming AEVs and corresponding efficiency of energy distribution during AEVs charging, such stations need to have a secure, resilient, and safety critical architecture and be supported by multi-level decision-making operation based on the developed analytical framework. As an application of energy distribution in SG, such architecture of charging station relies on available dynamic load scheduling techniques and utilizes the existing SG's telecommunication infrastructure supported by M2M communications and hybrid telecom networks.

The rest of the dissertation is organized as following. Chapter 2 describes the architecture and characteristics of smart grids (SGs) focusing on the performed standardization approaches; interoperability models for interfaces between SG domains; and the essential components of SGs: energy sources, energy consumers, and energy service providers. Chapter 3 describes hybrid telecom networks that can be implemented in SGs focusing on telecommunication technologies and protocols, intelligent machine-to-machine (M2M) communications, and applications of Internet of Things (IoT) and hybrid optical networks in telecommunication infrastructure of SGs. Chapter 4 presents the concept of dynamic energy distribution and management from various perspectives: dynamic demand estimation and response as an application of IoT implementation in SGs; dynamic load scheduling focusing on residential energy user domain; and demand-based energy generation. In addition to that, an opportunity to improve benefits of dynamic load scheduling based on high temporal sampling of load profiles in residential energy user domain has been introduced though developed mathematical model and performed simulation experiments in chapter 4. As an innovative application of demand energy management, a resilient and secure layered architecture of automated charging station for unsupervised electric vehicles have been proposed in chapter 5. Servicing flow with layered structure, analytical framework, and online scheduling procedure following by illustrative example have been presented in chapter 5 for the proposed architecture of automated charging station. In addition to that, simulation implementation of the proposed charging station's operation though an analytical platform has been performed in chapter 5. Several simulation experiments have been conducted to demonstrate an example of analysis of charging station's operation.

CHAPTER 2: ARCHITECTURE AND CHARACTERISTICS OF SMART GRIDS

2.1 Definition of a Smart Grid and Conceptual Model

A traditional energy grid is generally described as an interconnected network for transmission and distribution of electricity from generation sites to the consumers' domains. In the course of the conventional development of traditional energy grids, the electric power industry had devoted more attention and resources to power generation and transmission networks rather than to power distribution networks, as shown in FIGURE 1. This process occurred due to conventional paradigm that the demand for electricity completely dictates its generation [33-36]. As a result, bulk generation plants and power transmission systems have been traditionally monitored and controlled using legacy communication networks allowing a certain level of centralized coordination. Whereas, power distribution grids have been traditionally passive systems with limited communication capabilities. This fact significantly reduced flexibility, sustainability, and efficiency of traditional energy grids (FIGURE 1) [33-36].

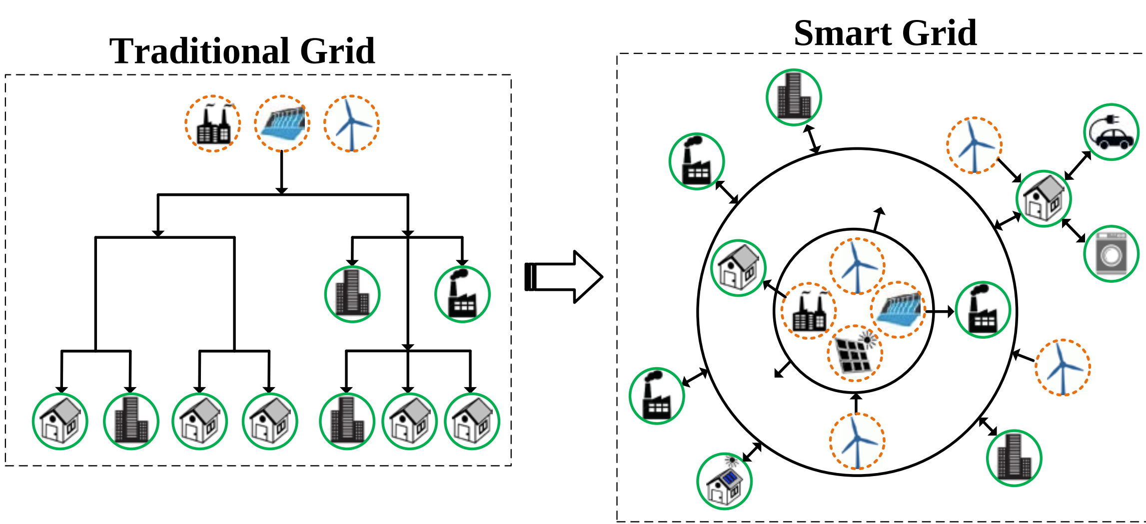

FIGURE 1: Transition from traditional grids to smart grids.

In comparison with traditional energy grids (FIGURE 1), a smart grid (SG) represents a true revolution in energy distribution and supply. On one side, the SG paradigm modernizes the traditional energy grids through self-healing (ability of a network to quickly repair itself in the event of any external or internal disturbances), automation, and remote monitoring and control [37]. Besides, the SG paradigm educates consumers about their energy usage, costs, and alternative options, to enable autonomous decision making about how and when to use electricity and fuels [37], [38-40]. Therefore, users' domains of a SG play an important role in energy distribution process, which involves a wide variety of technologies and numerous standards developed to ensure reliability and interoperability [35, 36, 38-40]. In addition to that, the SG provides safe, secure, and reliable integration of distributed and renewable energy sources to support consumers' comfort experience and protect environment [37]. All these enhancements define a SG as "an electric system that uses information, two-way, cyber-secure communication technologies, and computational intelligence in an integrated fashion across electricity generation, transmission, substations, distribution and consumption to achieve a system that is clean, safe, secure, reliable, resilient, efficient, and sustainable" [36].

During the SG standardization process, the Smart Grid Interoperability Panel (SGIP) at the National Institute of Standards and Technology (NIST), a private/public partnership funded by different industry stakeholders in cooperation with the United States federal government, focused on the development of a framework for coordinating all SG stakeholders and accelerating standards harmonization and interoperability [40]. As a first step of this development, the SGIP established the SG conceptual model, illustrated in FIGURE 2. The first version of this conceptual model was published in January 2010 [40], and it was reviewed and updated in February 2012 [39]. The NIST report describing the SG conceptual model identifies about 80 existing standards that can be used to support SG developments. Besides, this report identifies high priority gaps, for which new or revised standards are directly needed [38-40].

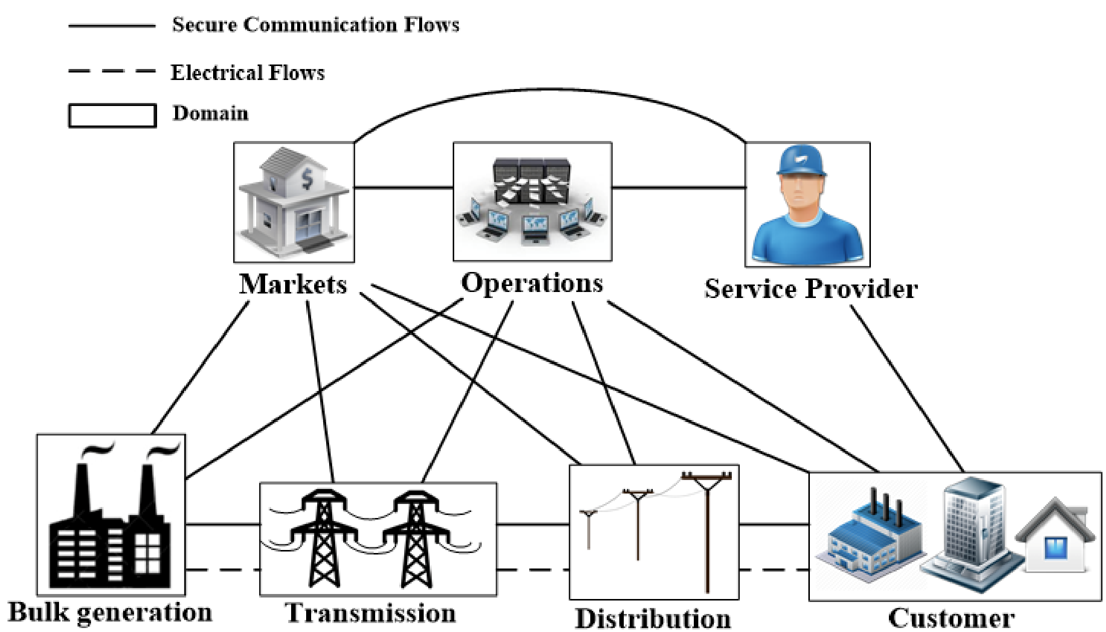

FIGURE 2: NIST Smart Grid Conceptual Model.

As shown in FIGURE 2, the SG conceptual model defines seven domains as well as the electrical and communication flows among them [39]. The electrical flows involve the traditional subsystems of the electrical grid: bulk generation, transmission, distribution, and customer domains. Communication and information data flows create a mesh topology between almost every domain illustrating the outstanding importance of communications in the SG [39, 40]. Based on the terminology developed for this conceptual model, each domain and its subdomains encompass SG "actors" and "applications." Actors include devices such as smart meters, data concentrators, various buffers; systems, e.g., energy consumption measurement and control; programs; and stakeholders that make decisions and exchange information. Applications are tasks performed by one or more actors within a domain (home and building automation, etc.) [39, 40].

TABLE 1: Domains and actors in the NIST Smart Grid conceptual model [39].

Domains	Actors
Bulk generation	Power plants—generators of electricity in bulk quantities
Transmission	Transmission system operators—carriers of bulk electricity over long distances
Distribution	Distribution system operators—distributors of electricity to and from customers
Customer	End users of electricity able to generate, store, and manage their energy utilization
Operations	Managers of the power flow to and from customers
Markets	Commodity markets that specifically control the trade and supply of energy (actors from independent system operators and regional transmission organizations)
Service providers	Energy services companies—organizations providing services to electrical customers and utilities (aggregators, retailers, etc.)

A specific design of a SG can be obtained by implementation of a conceptual model for a given domain, a given application, its specific requirements, the actors involved in this application, and the description of interactions between the actors. TABLE 1 summarizes the main actors included in each domain of the SG conceptual model and summarizes their typical functionality and roles [39]. The corresponding diagrams presented at FIGURES 3 - 9 are used to provide a quick visual and comprehensive functionality.

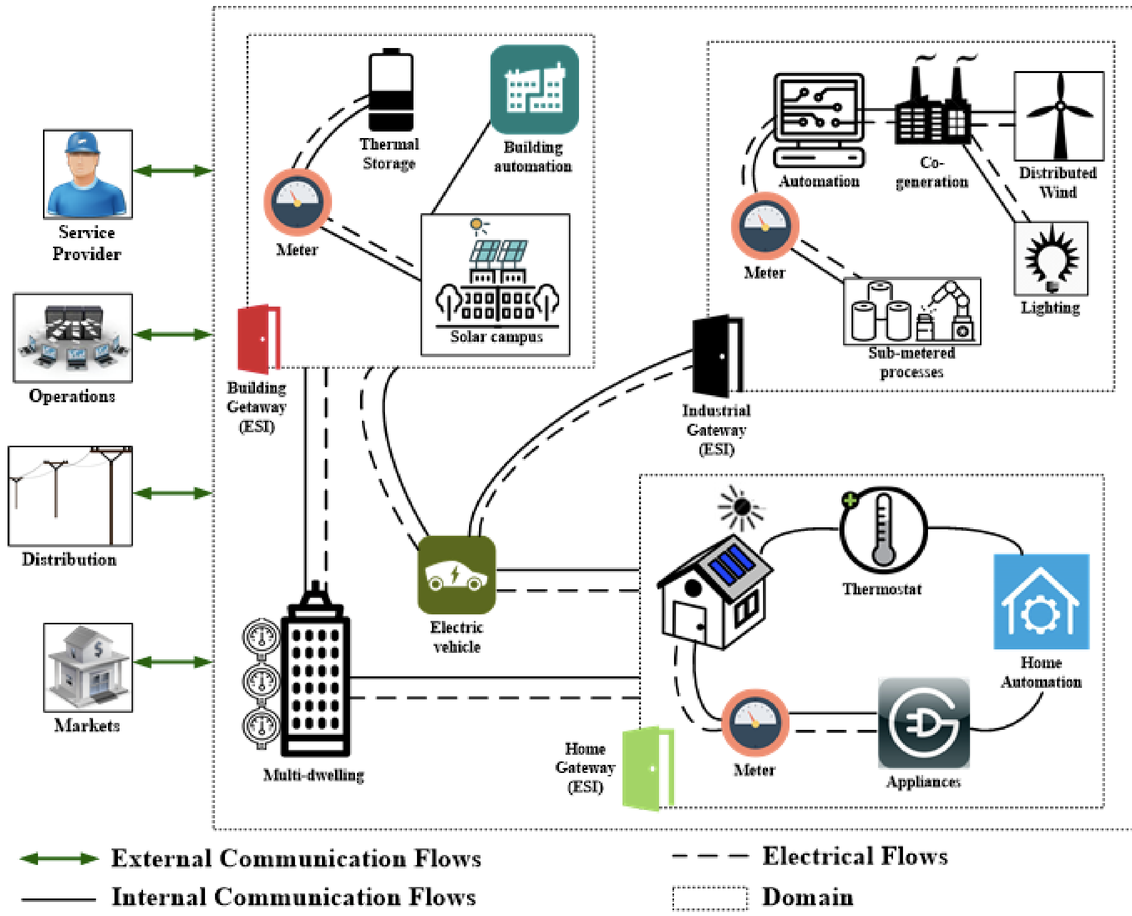

FIGURE 3: General architecture of the customer domain.

The customer domain of the SG conceptual model (FIGURE 3) is an energy consumption domain that consists of stakeholders supported by the entire infrastructure of a SG [39]. The actors in this domain are smart meters, Internet of Things (IoT) sensors, and other intelligent electronic devices (IEDs) such as circuit breaker controllers, capacitor bank switches, load tap charger controllers, etc. [37, 41]. These actors can manage consumers’ energy usage and its generation and control the information flow between the customer domain and other domains of the SG conceptual model (see FIGURE 3). To perform these tasks, several actuators are used in the customer domain, such as home and building automation systems. Utility meters and energy service interfaces (ESIs) are the boundaries of the customer domain (FIGURE 3). More details about energy consumers within the SG will be discussed in Subsection 1.4.2.

The markets domain is a part of the Smart Grid (SG) conceptual model (see FIGURE 2), where energy grids assets are bought and sold (e.g., FIGURE 4) [39, 40]. The main functions of this domain are energy price exchange and balance of supply and demand within the power system. The boundaries of the markets domain are at the edge of the operations domain controlling the SG, the domains of supplying assets, such as generation and transmission, and the customer domain as depicted at FIGURE 4 [39]. Communication flow, e.g., transmission of signals for load monitoring and control, pricing information, etc., between the markets domain and all other domains must be reliable, traceable, and auditable to ensure an efficient matching of energy production with its consumption. Besides, these communications must support e-commerce standards for integrity and non-repudiation. The participation of distributed energy resource (DER) in the markets domain is persistently increasing and becomes more interactive [35, 36, 42].

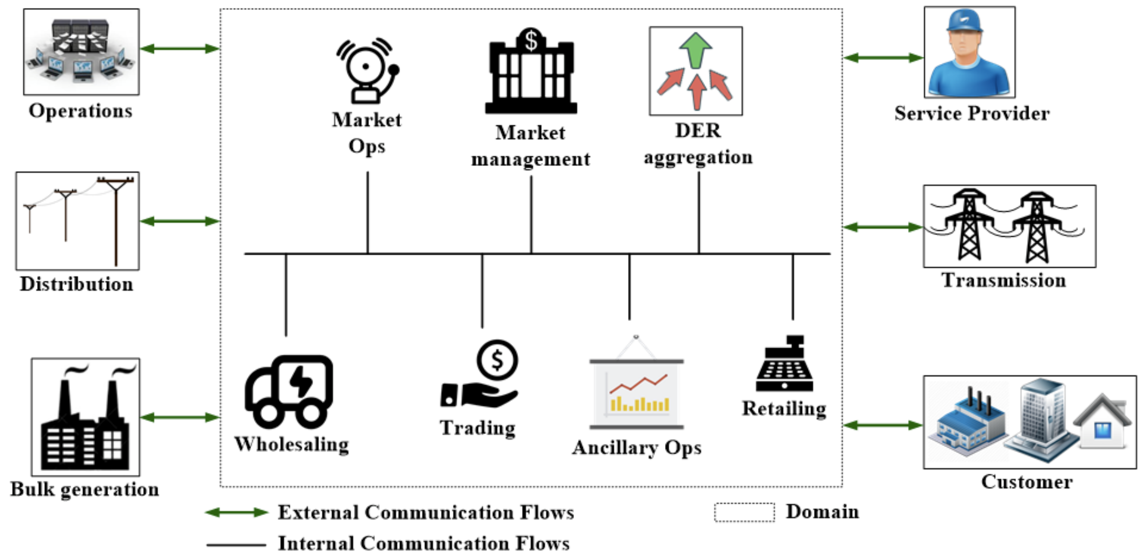

FIGURE 4: General architecture of the markets domain.

According to the SG conceptual model shown at FIGURE 2, the service provider domain depicted at FIGURE 5 shares interfaces with the markets, operations, and customer domains. Communication flow between the markets domain and the other domains is very critical for each domain connected to the service provider: operations by system control and awareness, markets and customer by the grid's efficiency enabling its economic growth and development of "smart" services [39, 40]. In the service provider domain, illustrated in FIGURE 6, actors perform services to support business processes of power system producers, distributors, and customers. The examples of these processes are billing and customer account management, management of energy use, home energy generation, etc. [43]. More details about service providers within the SG will be given in Subsection 1.4.3.

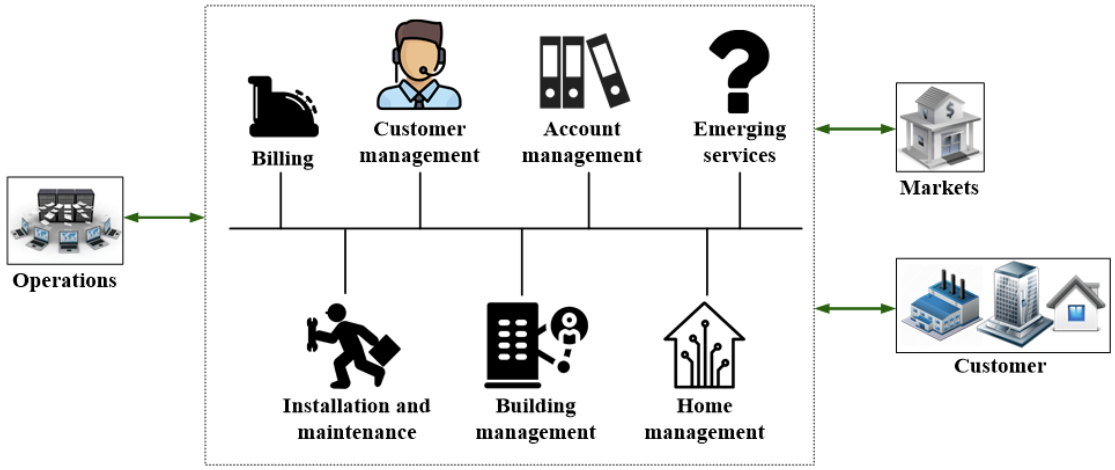

FIGURE 5: General architecture of the service provider domain.

According to the SG conceptual model shown at FIGURE 2, the operations domain has secure communication connections with all other domains of a Smart Grid (see FIGURE 6) [39]. The operations domain is responsible for the smooth operation of the power system [39, 40]. Controlling planning and service delivery processes, this domain supplements the functionality of the service provider and market domains [39, 40].

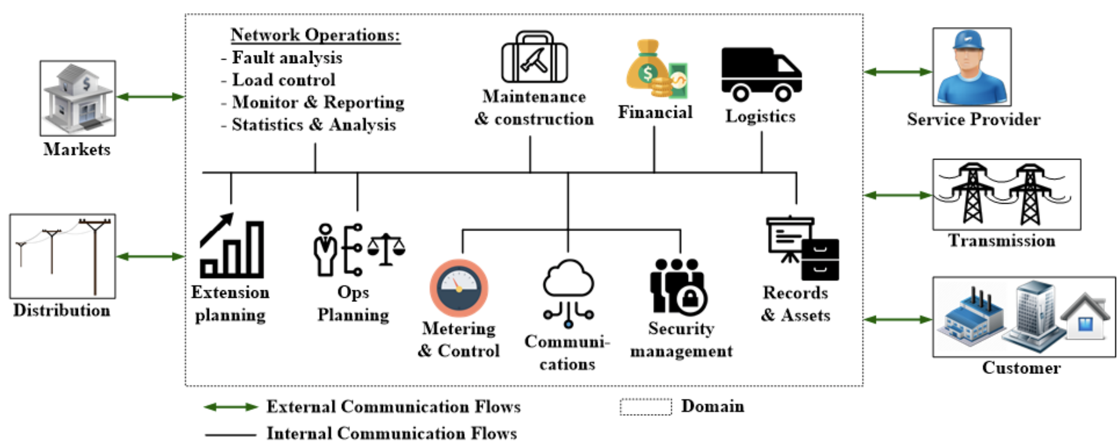

FIGURE 6: General architecture of the operations domain.

The generation domain, illustrated in FIGURE 7, is electrically connected to the transmission or, in some cases, to the distribution domain and shares communication interfaces with the operations, markets, transmission and distribution domains (see

FIGURE 2) [39, 40]. The generation domain communicates information about performance and quality of service of variable energy sources, which can be renewable or non-renewable (e.g., FIGURE 7). In this domain, electricity is produced from other forms of energy, which may include a wide variety of sources: chemical combustion, nuclear fission, water flow, wind, solar radiation, and geothermal heat (FIGURE 7) [39, 40]. Therefore, applications in the generation domain are the first processes in the electricity delivery to Smart Grid's customers. Besides, various physical actors are presented in this domain: protection relays, remote terminal units, equipment monitors, fault recorders, user interfaces, and programmable logic controllers. The boundaries of the generation domain are either the transmission or the distribution domain [39, 40].

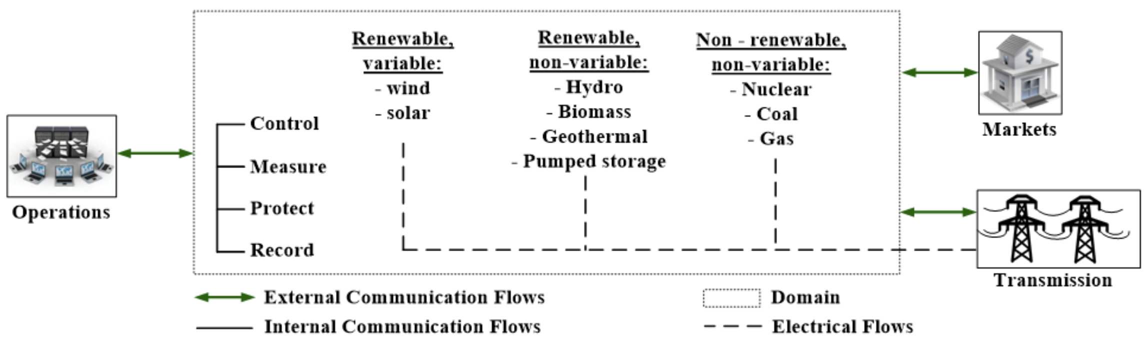

FIGURE 7: General architecture of the generation domain.

The transmission domain of the SG conceptual model (see FIGURE 2) performs bulk transfer of electrical power from the generation to the distribution domain through multiple substations (see FIGURE 8) [39, 40]. The transmission domain is typically operated by a transmission-owning utility, which can be represented by a regional transmission operator (RTO) or an independent system operator (ISO). The main responsibility of the RTO or ISO is to maintain stability of the electric grid by balancing energy generation with its load across the transmission network. The physical actors of the transmission domain depicted at FIGURE 8 are remote terminal units, substation meters, protection relays, power quality monitors, phasor measurement units, sag monitors, fault recorders, and substation user interfaces [39, 40].

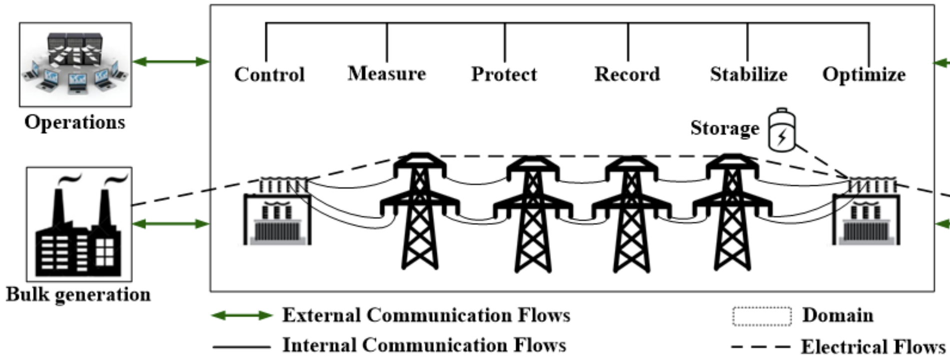

FIGURE 8: General architecture of the transmission domain.

As it was described previously, the Smart Grid concept brought decentralization to the energy distribution component of the electric power system. Because of this, many communications and electrical interfaces are considered to work in both directions supporting a bidirectional flow. Based on these considerations, the general architecture of the distribution domain was developed (FIGURE 9) [39, 40]. In such architectural design, distribution actors may have local peer-to-peer communication with more centralized communication methodology in several cases [36, 39, 40, 42].

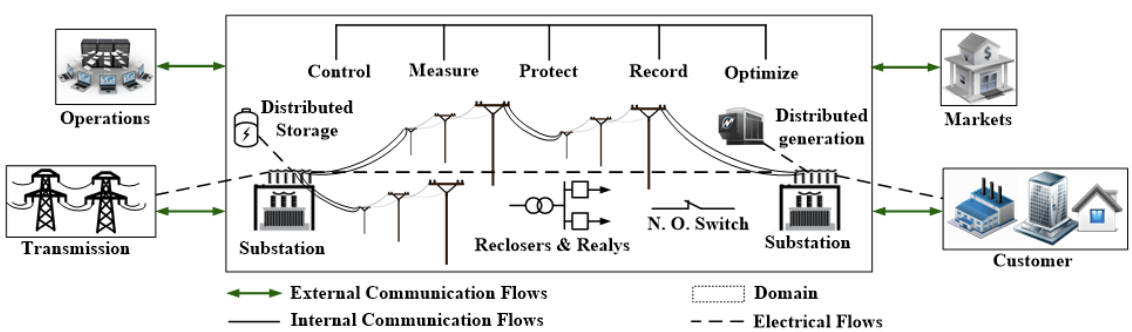

FIGURE 9: General architecture of the distribution domain.

In the Smart Grid, the distribution domain will communicate in real time more closely with the operations domain to manage the power flow associated with a more dynamic markets domain [39, 40]. The markets domain will communicate with the distribution domain in ways that will affect localized consumption and generation. In turn, these behavioral changes in consumption and generation due to market forces may have electrical and structural impacts on the distribution domain and the larger grid [39, 40]. In this architecture, service providers may communicate with the customer domain using the infrastructure of the distribution domain. The typical applications within the distribution domain are usually divided into the following categories: substation monitoring and control, management of energy storage unit, management of distributed generation, and control of SG's protection and optimization mechanisms [39].

2.2 Standardization Approach in Smart Grids

In addition to the SG conceptual model [39], the other main outcomes of the Smart Grid Interoperability Panel (SGIP) activities are the elaboration of standards, practices, and guidelines that allow the development and deployment of a robust and interoperable SG. As a result, in May 2011 the SGIP governing board established the Catalog of Standards (CoS). This CoS was updated several times and is available online through the National Institute of Standards and Technology (NIST) SG Collaboration [44]. As of today, the CoS comprises 20 individual standards and five separate series containing 36 additional standards, which accounts for a total of 56 standards.

Besides the International Electrotechnical Commission (IEC), other technical professional organizations (see TABLE 2) have introduced their own standards and recommendations for development of a SG conceptual model. The prevalent contribution was done by the IEEE, which has more than 100 standards relevant to smart grids. Among them, over 20 IEEE standards were included in the NIST “Framework and Roadmap for Smart Grid Interoperability Standards,” known collectively as Release 3.0, which was issued in 2014. The major standards from this document are listed in TABLE 2.

TABLE 2: Standards identified by NIST Framework and Roadmap for Smart Grid Interoperability [38]

Standard		Application	Domains of SG
ANSI	C12.1	Establishes acceptable performance criteria for new types of smart meters, demand meters and registers, pulse and auxiliary devices. Describes acceptable in-service performance levels for meters and devices used in revenue metering.	Customer, Service Provider
	C12.18	Revenue metering End Device Tables.	Customer, Service Provider
	C12.19	Electricity Meters - 0.2 and 0.5 Accuracy Classes.	Customer, Service Provider
	C12.20	Transport of measurement device data over telephone networks.	Customer, Service Provider

	C12.21 /IEEE 1702	Protocol and optical interface for measurement devices.	Customer, Service Provider
	/ASHRAE 135/ISO 16484-5 BACnet	Defines an information model and messages for building communications at a customer's site. Incorporates a range of networking technologies, using IP protocols, to provide scalability from very small systems to multi-building operations that span wide geographic areas.	Customer
IEC	60870-6 - 503	Performs Telecontrol Application Service defining the messages sent between control centers of different utilities.	Transmission, Distribution
	60870-6-702	Defines a standard profile specifying which services and objects are mandatory and optional for compliance with the standard for implementing the application, presentation, and session layers. For a complete protocol implementation, this profile links to a connection-oriented transport profile specifying the transport, network, and data link layers.	Transmission

	60870-6-802	Formerly known as Inter Control Center Protocol (ICCP), the standard is used for communication of electric power system status and control messages between power control centers.	Transmission
	61850 Suite	Defines communications within transmission and distribution substations for automation and protection. It is being extended to cover communications beyond the substation to integration of distributed resources and between substations.	Transmission, Distribution
	61968/61970 Suites	Define information exchanged among control center systems using common information models: application-level energy management system interfaces and messaging for distribution grid management in the utility space.	Operations
IEEE	1815 (DNP3)	Used for substation and feeder device automation, as well as for communications between control centers and substations.	Generation, Transmission, Distribution, Operations, Service Provider

	C37.118.1/2	Defines phasor measurement unit (PMU) performance specifications and communications for it.	Transmission, Distribution
	C37.238	Ethernet communications for power systems	Transmission, Distribution
	C37.239	Defines a common format for interchange of power system event data	Transmission, Distribution
	1547 Suite	Defines physical and electrical interconnections between the grid and distributed generation and storage.	Transmission, Distribution, Customer
	1588	Standard for time management and clock synchronization across the Smart Grid for equipment needing consistent time management.	Transmission, Distribution
	1901/ ITU-T G.9972	Broadband over Power Line Networks for home networking: Medium Access Control and Physical Layer.	Customer
NAESB	REQ18, WEQ19	The standards specify two-way flows of energy usage information based on a standardized information model.	Customer, Service Provider
NAESB	REQ-21	Enables retail customers to share energy usage information with third parties who have acquired the right to act in this role.	Customer, Service Provider

OASIS	Energy Interoperation	An information model and a communication model to enable demand response and energy transactions.	Markets
	Energy Market Information eXchange	An information model to enable the exchange of energy price, characteristics, time, and related information for wholesale energy markets, including market makers, market participants, quote streams, premises automation, and devices.	Markets
NEMA SG-AMI		Used by smart meter suppliers, utility customers, and regulators to guide both development and decision making in smart meter upgradeability.	Customer, Distribution
OPC-UA Industrial		A platform-independent specification for a secure, reliable, high-speed data exchange based on a publish/ subscribe mechanism	Customer
Open Automated Demand Response (OpenADR)		Specification of messages exchanged between the Demand Response (DR) Service Providers and customers for price-responsive and reliability-based DR.	Operations, Service Providers

CEA-852.1	Provides a way to tunnel local operating network messages through an IP network using the User Datagram Protocol (UDP), thus providing a way to create larger internetworks	Customer, Service Provider
Smart Energy Profile 2.0	Home Area Network (HAN) Device Communications and Information Model.	Customer

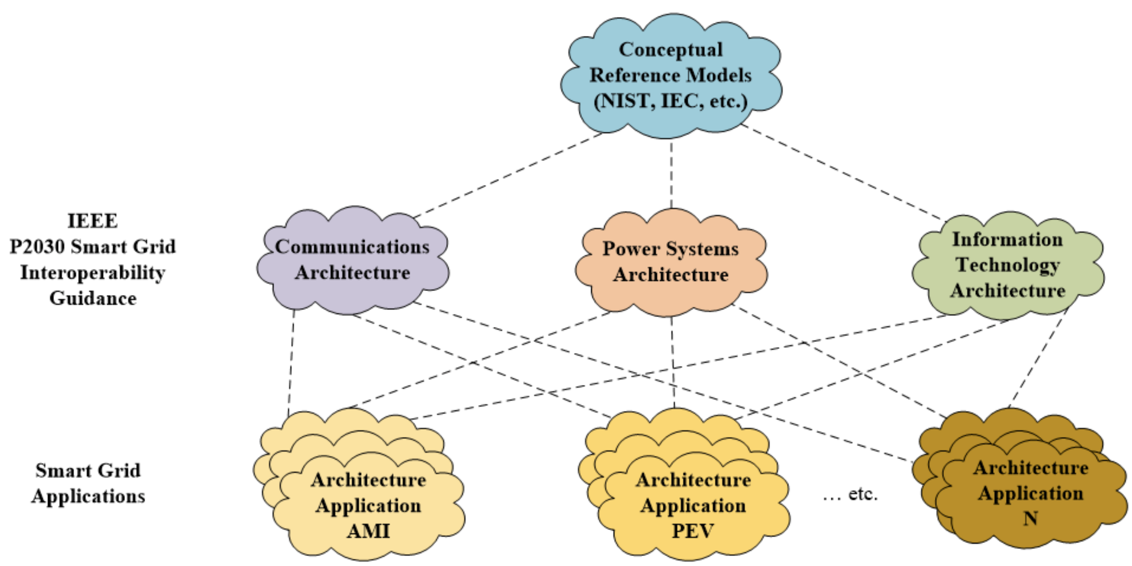

FIGURE 10: Scope of IEEE 2030 standardization process.

The scope of IEEE 2030 standardization and overall reference architecture is illustrated in FIGURE 10 [45]. As described previously, the standardization process was initialized by conceptual reference models, such as NIST's Smart Grid conceptual model (see FIGURE 2) [38, 39]. To ensure the SG's interoperability, this process occurred in three architectural perspectives: communications, power systems, and information technology. As a result, various applications were created in a Smart Grid: advanced metering infrastructure (AMI), charging of plug-in electric vehicles (PEVs), etc. (see FIGURE 10).

To define and elaborate upon such diverse functionality, a Smart Grid interoperability reference model (SGIRM) was created.

2.3 Smart Grid Interoperability and Architecture

Once a conceptual model of the SG was defined (see FIGURE 2) [39, 40], a reference architecture elaborating this model would be required. This architecture would define functional blocks and interfaces, thus bringing the developed conceptual model closer to implementation. IEEE’s project 2030 pioneered in developing such reference architecture following the standardization process displayed in FIGURE 10 and led to the SG interoperability reference model (SGIRM), well known in the community [45]. The SGIRM extends the NIST SG conceptual model defining three interoperability architectural perspectives (IAPs). IAPs represent the main areas of expertise involved in the SG: power systems (PS-IAP), information technology (IT-IAP), and communications technologies (CT-IAP) as depicted in FIGURE 10 [45]. Each IAP defines the main functional blocks required in each domain of the NIST SG conceptual model, the interfaces between functional blocks (intra-domain interfaces), and the interfaces between domains (inter-domain interfaces) [46]. The defined IAPs are further elaborated for the most important applications in the SG area, such as advanced metering infrastructures (AMIs) or plug-in electric vehicles (PEVs).

Being the main focus of this research, CT-IAP defines the communication networks that can be used in every domain. Communications networks domains and interfaces defined for the SG in IEEE's project 2030 are listed and described in TABLE 3 [45, 46].

TABLE 3: Communications networks defined for the SG in the IEEE 2030 CT-IAP [45, 46].

Communications Network	Description
xAN with energy services interfaces (ESIs)	Home area network (HAN), building area network (BAN), and industrial area network (IAN) encompassing all the intelligent electronic devices (IEDs) that allow monitoring and control of energy status and patterns within each context. ESIs represent logical gateways.
Neighborhood area network (NAN)	Last mile communications network that connects ESIs and smart meters, distributed energy resources (DERs) and microgrids to the utility control and operation center through the backhaul network
Backhaul	Backhaul network provides connectivity between the utility control and operation center and any communications network within the distribution, long-haul, and customer domains

The SG architecture model is the other representation of functional architecture of the SG that was developed by the Smart Metering-coordination Group (SMG) of the European Commission (EC) according to mandate M/490 [47]. According to SMG, the SG architecture model is defined as a three-dimensional architectural model comprising the domains, zones, and layers as displayed in FIGURE 11 [48]. The SG architecture model allows a technologically neutral representation of all the interoperability cases of the SG. The five defined layers of this model represent (top to bottom) the business objectives and processes, the functions, information exchange and data models, communication technologies and protocols, and its physical and logical components (see FIGURE 11). The communication layer, the main focus and the core of the current research, is developed in a separate document [49]. This document defines the communications networks and their deployment at the component layer and maps the identified technologies and protocols onto these networks.

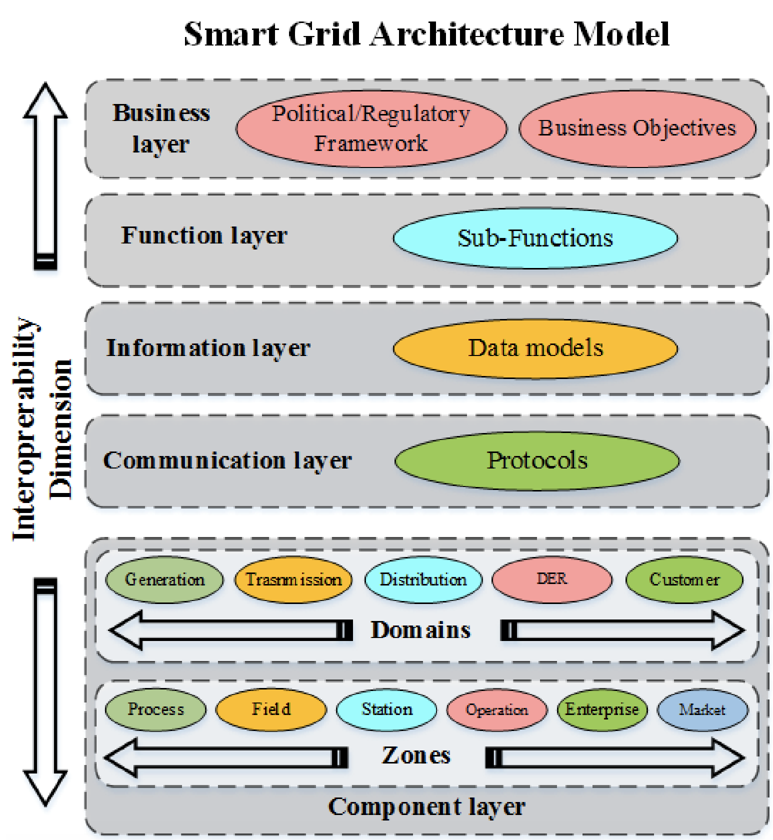

FIGURE 11: Smart Grid architecture model. The component layer refers to the domains of the SG conceptual model (see FIGURE 2).

In spite of the fact that the SG architecture model was initially created to describe the functional architecture of the SG, it appears to be a well-formed conceptual model of the power system expanding the initial one developed by the NIST. Specifically, this SG architecture model includes domains from its central generation down to customers, zones of operation from individual processes up to the managing enterprise and the market, and with interoperability layers covering a whole SG system from the business layer down to smart grid components.

2.4 The Essential Components of Smart Grids

2.4.1 Energy Sources in the Smart Grid

In traditional power grids, electricity is generated by a few central energy sources and transmitted in a unidirectional fashion to a large number of users. In contrast, SGs use two-way flows of electricity supported by a bidirectional information transmission through an automated advanced network for distributed energy delivery [14, 15, 36, 39, 40, 50]. Besides traditional energy generation stations, SGs have distributed renewable energy sources (RESs) and supporting battery energy storage (BES). The majority of RESs are solar and wind energy sources. BES can be designed and made up using a variety of technologies [36, 51-53]. The most popular types of BESs are lithium-based, nickel-based, and sodium-based batteries [51, 52].

As mentioned earlier, electricity in SGs can also be transmitted back into the grid by its users [35, 36, 39, 40, 42]. As an example, SG's users with solar panels at their premises are able to generate energy and transfer it back into the grid. Such backward energy flow is important and advantageous in situations when SG becomes "islanded" due to power failures. Using such energy feedback received from SG's users, a SG can function reducing the level of its own energy generation [35, 36, 39, 40, 42]. However, the so-called backward flow of electricity from the user sites toward distribution grids is not simple or straightforward, contrary to the information and data grids—it requires compatibility of legacy hardware by upgrading and implementation of strict safety protocols based on specific quality of service requirements [35, 36, 42].

Distributed generation (DG) is one of the key components of the paradigm enabled by SG. DG takes advantage of distributed energy resources (DER) systems: solar panels, wind turbine farms, and gas/diesel generators. All DER systems are often small-scale power generators (typically ranging from few kW to 10,000 kW) with an improved power quality and reliability [14, 39, 40, 50, 54]. From an energy generation perspective, the SG is a localized grouping of electricity generators and loads, which can disconnect from the main grid so that DG can continue to supply users with energy without obtaining power from outside. Thus, the disturbances in the main grid can be isolated, and peak-shaving techniques [53, 55, 56] can be implemented. A study [57] from the International Energy Agency pointed out that a power system based on a large number of reliable small DGs can operate with the same reliability and a lower capacity margin than a system of equally reliable large generators.

A useful review of various distributed energy technologies such as microturbines (gas, diesel, etc.), photovoltaic panels, fuel cells, and wind power turbines can be found in Adinolfi et al. [58]. However, implementing DG in practice is not an easy scheme due to several reasons [35, 36, 51, 52, 59]. First, DG involves large-scale deployments of (renewable energy sources) RESs, whose energy production is a subject to wide fluctuations due to weather and climate conditions. It was shown that the generation patterns from RES are far from being equal during a certain time span [17, 22, 35]. Therefore, it is important to maintain an effective utilization of the DG in a way that is aware of the variability of the yield from RES. The second challenge of DG's implementation is that the average operation costs of distributed generators for producing one unit of electricity are often higher than those of traditional large-scale central power plants [1, 17, 22].

Considering DG's potential benefits on power quality, it is essential to conduct a systematic research on how to balance the high capital costs and the reliable power supplies available through a DG paradigm. Although there is a limited penetration of DG in today's power system, the future SGs are expected to adopt a large number of distributed generators to increase the level of decentralization of existing power systems [1, 17]. As predicted in Pellicer et al. [1], this process could include the following three stages:

1. accommodation of DG in the current power system;
2. introduction of a decentralized system of DG cooperating with the centralized generation system; and
3. delivery of most power by DG and a limited amount by central generation.

Since the localized DG enables the users to deploy their own generators, the large-scale deployment of DG will also change the traditional power grid design methodology, in which the generators are directly connected to the transmission grid (e.g., FIGURE 1). Due to such changes, a layer of energy generation and distribution control can be included between bulk generation and transmission.

The deployment of DG further leads to the concept of a virtual power plant (VPP), which manages a large group of distributed generators with a total capacity comparable to that of a traditional power plant [44]. A VPP is a cluster of distributed generators that is collectively run by a central controller. The concentrated operational mode of VPPs allows reduction of a peak electricity load (“peak-shaving”) and load-aware power generation at short notice [36, 44]. The last benefit leads to real-time load scheduling and capacity planning within a SG [14, 50]. A VPP cluster can replace a conventional power plant while providing higher efficiency and flexibility of energy distribution. Such advanced flexibility allows energy systems to react quicker to fluctuations in energy demand. Both benefits of VPPs (peak-shaving and load-aware generation) require complex optimization, control, and secure communication methodologies.

Recently developed VPPs have been examined in numerous research studies [60-63]. Anderson et al. [60] focused on the investigation and description of a suitable software framework that can be utilized for implementation of the VPP concept in future power systems. The importance of service oriented architecture in implementing VPPs was emphasized in this work. Lombardi et al. [61] focused on the optimization of VPP’s architecture. Using an energy management system for this optimization, a VPP can be controlled to minimize the electricity production costs and to increase the utilization of renewable energy. S. You et al. [62] proposed a market-based VPP, which uses bidding and price signal as two optional operations. In this model, a VPP provides individual distributed energy resource units with the access to current electricity markets. S. You et al. [63], proposed a generic VPP model running under a liberalized electricity market environment and attempted to provide a summary of the main functions that are necessary for the efficient operation of the developed VPP model. A current integration of vehicle-to-grid (V2G) and VPP technologies was investigated in Zhang [64, 65] as well. The architecture of V2G integrated in VPP was outlined providing a sketch of the distribution algorithm, and the associated optimization problem for the overall VPP system.

2.4.2 Energy Consumers in the Smart Grid

Conventionally, three types of users/customers' domains are considered within a SG paradigm: residential, commercial, and industrial [14, 15, 38-40, 54]. According to its definition, the residential domain consists of private dwellings (apartments, townhouses, etc.). The energy users within residential domains are single households, whose energy loads usually include the following set of appliances: washers, dryers, cooktops/ovens, dishwashers, water heaters, etc. The energy consumption level of a single residential user is typically less than 20 kW [14, 15, 39, 40]. It is common to combine residential users into clusters where energy management is performed by a single energy service provider [14, 15, 39, 40]. The commercial domain is formed by small- and medium-size businesses and enterprises: stores, restaurants, hotels, etc. The typical loads within commercial domains are commercial refrigerators, freezers and ovens, and HVAC systems of an entire building and a cluster. For a commercial user, the average level of energy consumption is about 20–200 kW [14, 15, 39, 40]. The industrial domain consists of plants, factories, and other manufacturing and engineering facilities with the following typical energy loads: heavy machinery, fabrication and manufacturing equipment, etc. Generally, the energy consumption level of a single industrial user is over 200 kW and less tolerant to fluctuations and load shedding [14, 15, 39, 40].

The boundaries of these domains are generally considered at utility meters, such as smart meters (SMs), typically equipped the energy services interfaces (ESIs). For each user within its domain, energy management and control is performed through a single SM connected to energy loads by means of intelligent devices and sensors [14, 15, 39, 40]. These ESIs are secure interfaces for interactions between the energy service provider (ESP) and energy users (see FIGURE 3). The ESIs were standardized during the development of the SG architecture model depicted in FIGURE 11. Besides, different domains can communicate through ESIs via the advanced metering infrastructure (AMI) or via another communication network implemented within a SG, such as an Internet infrastructure [15, 39, 54]. In other words, the ESI can act as a bridge between the ESP and facility-based systems, such as a building automation system (BAS) or an energy management system (EMS) located at the users' domains of a SG [15, 39, 54]. Therefore, each domain of users is equipped with a SM and an ESI that may reside in the SM, on the EMS, or in an independent gateway. In addition to that, the ESI allows each energy user to communicate with devices and systems located within the energy users' premises across a home area network or other LAN. In some cases, commercial and industrial users' domains encompass more than one energy management system (EMS) and, therefore, more than one communications path per energy consumer [15, 39, 54].

The EMS is the entry point for several applications running at the functional layer of the SG architecture model (see FIGURE 11): load control, monitoring and control of distributed generation, in-home display of customer usage, reading of non-energy meters, and integration with BASs and enterprises. The EMS provides users logging and auditing functions for cyber security purposes. Each user's domain is electrically connected to the distribution domain and to the ESP through a corresponding telecommunication network of an AMI. Besides, each users' domain communicates with the operations and market domains. Typical applications of an EMS within the customer domain are presented in TABLE 4.

TABLE 4: Typical applications of EMS within the users' domain.

Application	Description
Building/home automation	A system that is capable of controlling various functions within a building such as lighting and temperature control.
Industrial automation	A system that controls industrial processes such as manufacturing or warehousing.
Micro-generation	Includes all types of distributed generation including solar, wind, and hydro generators. Generation harnesses energy for electricity at a customer location. May be monitored, dispatched, or controlled via communications.

2.4.3 Energy Service Providers in the Smart Grid

To ensure an efficient energy management and its reliable delivery, users domains are required to be in close interaction with their ESP. Based on the developed SG Conceptual Model, an Energy Service Provider (ESP) or an energy service company (ESCO) can be defined as a commercial or non-profit organization providing solutions for energy supply and generation, designing and implementing projects for energy efficiency improvement, energy retrofitting and conservation [35, 42, 65-67]. The main role of ESPs' is to develop, design, build, and fund projects that produce, save energy, reduce energy costs, and decrease operations and maintenance costs at their customers' facilities [68]. In general, ESPs act as project developers for a comprehensive range of energy conservation measures, assuming the technical and performance risks associated within their projects.

ESPs are acting at the business layer of SG Architecture Model (in reference to FIGURE 11). Using the corresponding telecommunication connections and networks (see FIGURE 2), they collect information about current, predicted, and required statuses of energy generation, transmission, and distribution from operations domain of SG. Besides, the ESPs inquire the data from markets about current energy prices for each source of its generation and the information about users' requirements and preferences from Energy users' domains. All the data collected by the ESPs from various domains of a SG are utilized for continuous management of energy flow, which can be performed in real time [14, 15].

From a business point of view, ESPs are distinguished from other firms that offer energy-efficiency improvements in the fact that they use the performance-based contracting methodology: when an ESP implements a project, the ESP's compensation is directly linked to the actual energy cost savings. Many of the recent ESP's projects with substantial energy efficiency retrofits involve renewable energy technologies and advance energy distribution techniques. Typically, such projects require large initial capital investments and have a relatively long payback period. The substantial energy efficiency retrofits and renewable energy technologies inherent in energy savings performance contract (ESPC) projects typically require large initial capital investments and may have a relatively long payback period.

2.5 Summary

In this chapter, a definition and conceptual model of smart grid (SG) based on corresponding NIST standardization have been provided. In addition to that, SGs have been described from various perspectives: developed standardization approaches, interoperability and architecture models, and the essential components of SGs such as energy sources, energy consumers, and energy service providers. Smart grid paradigm modernizes traditional energy grids with self-healing, automation, remote control, and ability to manage energy consumption and generation for its efficient operation. Each domain of a SG is characterized by a tight integration of flexible and secure communication networks and a large number of sensors and actuators transforming it into an intelligent electricity network, with building blocks represented by machine-to-machine (M2M) communications enabling interconnection of various sensing devices within a SG.

CHAPTER 3: HYBRID TELECOM NETWORKS FOR SMART GRIDS

3.1 Telecommunication Technologies and Protocols in Smart Grids

Although there are varieties of communications technologies available for telecommunication infrastructures for the SG [69, 70], wireless ones are currently of special interest. These avoid wired connectivity and enable mobility and identity of the end users. As a token of that, NIST set up a specific working group within the Priority Action Plan 2 (PAP2) to tackle the challenges and opportunities of wireless communications in the SG paradigms [71]. Communications for the SG present specific requirements from both the technical and economic perspectives, such as described in [72-74]:

- Quality of Service (QoS) required for the target application. Generally, QoS can be defined by accuracy, with which different information can be delivered timely to the respective parties, and priorities for specific data transmission in SGs. Notably, QoS policies are mainly oriented to traffic prioritization and resource allocation to face congestion situations. Some parameters that are widely used to quantify such QoS level are:
  - ✓ Latency defined as the end-to-end delay of the data transmission. A general latency requirements for SG telecommunication networks are presented in the TABLE 5 below [69].
  - ✓ Bandwidth providing an aggregated data rate high enough to carry the traffic associated to the target application. In general, this would depend on the volume of devices as well as on the size of the exchanged packets and the traffic pattern.

- ✓ Reliability guaranteeing the correct performance during a given percentage of time: the more critical the application is, the higher such a percentage needs to be.

✓ TABLE 5: General QoS requirements for SG telecommunication network

Maximum latency	Communication Type
≤4ms	Protective relaying
sub-seconds	Wide area situational awareness monitoring
seconds	Substation and feeder supervisory control and data acquisition (SCADA)
minutes	Monitoring noncritical equipment and marketing pricing information
hours	Meter reading and longer-term pricing information
days/weeks/months	Collecting long-term usage data

- Interoperability allowing equipment from different manufacturers to interact seamlessly. In order to achieve this goal, the main functional blocks comprising the communications infrastructure and the interfaces among them must be defined and standardized. Standardization is crucial for effectively achieving this goal, which eventually fosters competition and thus yields more reliable products at lower cost.
- Scalability dictates that the communication architecture must be able to incorporate new services, devices and infrastructure upgrades. This requirement is crucial for integration of emerging energy services such as charging stations for electric vehicles and drones [32, 75], wireless charging [6, 27, 76], etc.

- Security presented in the form of both physical and cybersecurity. In SGs, various aspects of users' privacy, such as identification, authorization, and access control, are considered [74, 77, 78]. Therefore, impersonation, data tampering, malicious software, denial of service, and cyberattacks need to be addressed as main security issues in SGs [79]. Along with security.
- Privacy is a major concern for data transmission in SGs [77]. Initiatives for data privacy in SGs provide a multi-metrics approach to calculate system's privacy and dependability levels [80]. Additionally, pseudo-nymizing (or differential privacy) and cryptographic computation approaches can be used for preserving privacy for IoT-enabled SGs [81]. An elliptic curve cryptography (ECC) based session key technique was introduced to implement these approaches and gain an efficient authentication and access control [82].

Since SG applications handle sensitive data, security and privacy represent key factors for their wide deployment and adoption. If privacy is not guaranteed, many users will not embrace the various new services. If security is not guaranteed, many service providers would not be implemented or rely on such new services. However, privacy and security are usually directly proportional to costs, so a trade-off would be required in order to obtain feasible solutions. As a result, it is crucial to evaluate how different communication architectures and technologies meet such requirements before undertaking the important investments needed to deploy infrastructures on a large scale.

Recently, several divergent standards and protocols have been proposed for SG communication. Each protocol focuses on a specific aspect of SG communication [83]. The lack of a protocol that can satisfy the heterogeneous requirements of various communication types in a SG has resulted in a highly fragmented protocol stack in SG telecommunication systems as summarized in TABLE 6. Considering the variety in operating conditions and QoS requirements, it is impossible to depend on one protocol for all data streams or all SG applications. The core question that could be raised here is which transport protocol should be selected for a certain SG application. In different studies [83-86], the introduced platform enables the dynamic adaptation for transporting heterogeneous traffic of SG applications and mediation with available telecommunication platforms.

TABLE 6: Protocol stack in SG telecommunication system [83].

<table>
<tr><td rowspan="2">Application layer</td><td colspan="8">REST/SOAP/SIP</td></tr>
<tr><td colspan="3">HTTP/HTTPS</td><td colspan="4">MQTT/STOMP/AMQP</td><td>CoAP</td></tr>
<tr><td>Transport layer</td><td colspan="6">TCP RCF 793</td><td colspan="2">UDP RCF 768</td></tr>
<tr><td>Network layer</td><td colspan="2">6LoWPAN RCF 4944</td><td>IPsec RCF 2401</td><td colspan="4">IPv4 RCF 791,
IPv6 RCF 2460</td><td>DSCP RCF 2474</td></tr>
<tr><td>Physical and data link layer</td><td>IEEE 802.15.4</td><td>Bluetooth v4.0</td><td>IEEE 802.3</td><td>WLAN 802.11</td><td>WiMax IEEE 802.16</td><td>2.5G GPRS</td><td>3G UMTS</td><td>4G LTE 3GPP TF25.913</td></tr>
</table>

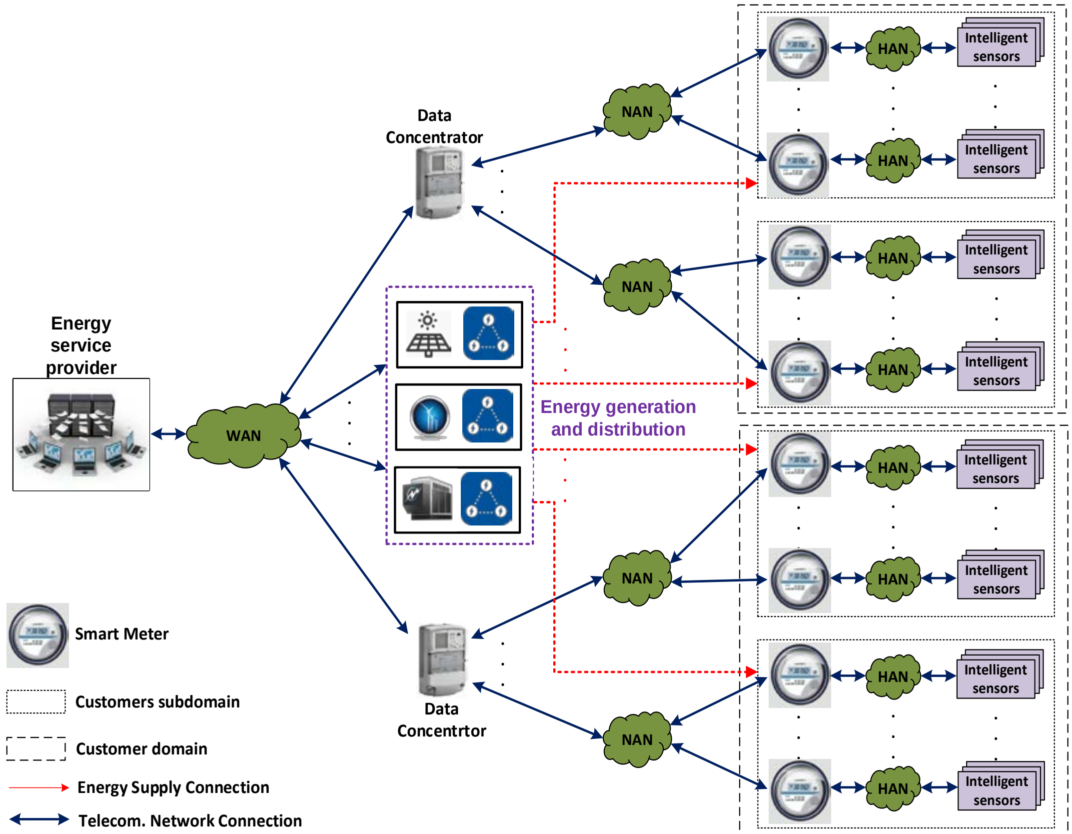

FIGURE 12: General example of telecommunication network supporting advanced metering infrastructure of SGs. Data from each customer domain is obtained through corresponding data concentrators and NANs, which consist from several HANs that are monitored by smart meters. WAN controls energy generation and distribution for the whole grid.

From a structural point of view (cf. FIGURE 12), the telecommunication network of a SG consists of three parts, namely, wide, neighborhood, and access area networks (WAN, NAN, and HAN respectively) [14, 15, 38-40]. Each segment of such networks transmits different amounts of data, which increases from the smallest (within HAN) to the largest (within WAN), and has a corresponding bandwidth capacity.

As a mainstay, WANs support bidirectional communication that maintains distributed automation and power quality management for the whole SG. All power generation stations, substations, and transformers as well as data concentrators communicate with the energy service provider (ESP) through the WAN (FIGURE 12). Such a network can be deployed/configured using several wired or wireless broadband technologies, listed in TABLE 7 [15, 54, 87, 88]. For all these technologies, the transmission bandwidths are determined by underlying protocols and often vary over a wide range, e.g., from 172 kb/s for GPRS to 10 Gb/s for 10G EPON [54, 87, 88]. A final choice of communication technology for the WAN would depend on the particular requirements of the SG's design. The physical connection is often presented by wireless, copper, and optical fiber media. The medium access control (MAC) is mostly used to form a communication link.

Deployed in a single user domain, HANs offer users a convenient capability for direct power demand and response management through monitoring and control of the intelligent devices described above. In most cases, such demand management can be performed through the usage of smart meters (SMs) as gateways to the utility (FIGURE 12) [44, 46, 54, 87, 88]. In spite of the fact that SMs vary in communication technology and design, they support an information flow through a simple general principle: acquire data (such as measurements of voltage, frequency, current and power) from connected sensors and actuators, send this data to a control point, which is usually located at the ESP site, and receive the corresponding response from the control point [15, 54, 87, 88]. In such data transmission process, data concentrators are intermediate nodes utilized for temporal storage and preprocessing of information. At the same time, the interfaces of data concentrators are utilized for energy demand management application. For this demand management, a meter data management system (MDMS) application is used from users' end. Since the amount of data generated within a single user system is quite small, most of the technologies implemented at HAN have a limited bandwidth [54, 87, 88], as summarized in TABLE 7.

NANs are central entities of an advanced metering infrastructure (AMI) to provide the information, obtained by SMs and collected by data concentrators, to the WAN (FIGURE 12) [36, 39, 40, 54, 87, 88]. Most common communication technologies implemented in NAN are listed in TABLE 7. All of these technologies use open standards to provide scalability and flexibility for SG communications and can be developed for small range coverage networks [54, 87]. Similar to WAN, the implemented protocols define the neighborhood area network (NAN) transmission bandwidth that has currently an upper limit of 1 Gb/s.

TABLE 7: Telecommunication media and protocols for three structural parts of SGs.

WAN	NAN	HAN
Wi-MAX (IEEE 802.16)	LoWPAN (IEEE 802.15.4) / PLC (IEEE 1901) / G.hn / Homeplug / Cellular / WLAN (IEEE 802.11 a/b/g/n)	
OTN, SDH, SONET	GPON	ADSL

3.2 Intelligent Machine-to-Machine Communications in Smart Grids

3.2.1 Reference Architecture of Machine-to-Machine Interactions

Machine-to-Machine Interactions (M2M) interactions are generally defined as a direct communication between devices using any available data transmission channel. M2M interactions enable various sensors or meters to communicate the sensed and recorded data to application software that can utilize this data to adjust certain industrial or manufacturing process [89, 90].

FIGURE 13 displays the central domains of the M2M reference architecture developed by European Telecommunications Standards Institute (ETSI) [91]. This is a resources-based, end-to-end architecture of M2M interactions identifying the functional entities and the related reference points. The M2M reference architecture can be used for the exchange of data and events between machines and entities involving communications across networks without requiring human intervention.

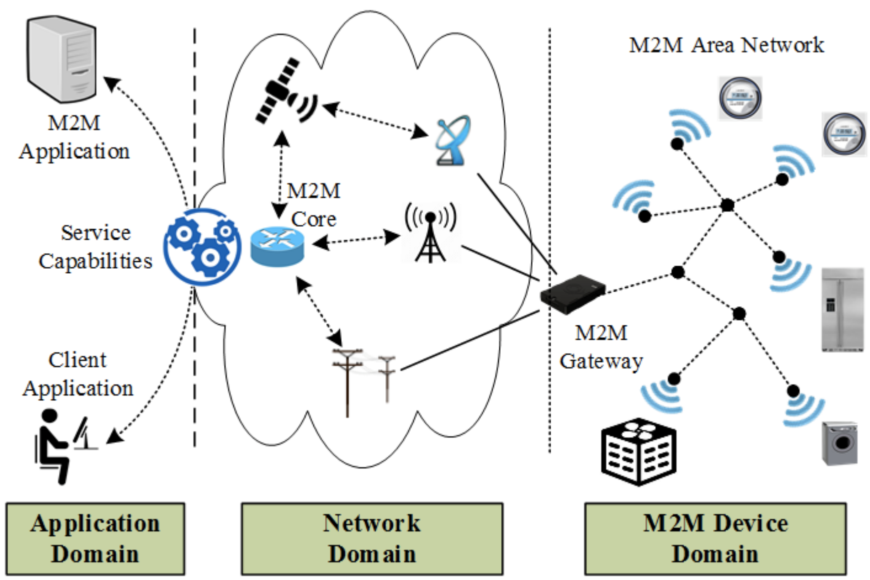

FIGURE 13: Main domains of the M2M reference architecture according to European Telecommunications Standards Institute.

At the reference architecture (FIGURE 13), M2M interactions are described as a distributed system with service capabilities at both network and the M2M device domains level. These capabilities are defined in the specification and are used to put in communication applications, e.g., network, gateway, and device domains. The M2M device domain encompasses the so-called capillary networks (in ETSI terminology), i.e., the sensors and actuators networks (SANs) [33]. The network domain represents the core of the

M2M infrastructure and provides bidirectional bulk data exchange over long distances. Finally, the application domain encompasses the services, which are delivered on the top of the M2M infrastructure.

There are multiple functions that can be supported in a SG by intelligent M2M communications: smart metering, distribution and transmission control, etc. Smart metering in M2M interaction can facilitate flexible demand management where smart meters are two-way communicating devices that measure energy consumption and transmit that information via some information and communications technology (ICT) back to the local utility. With near real-time information available (e.g., the flow of energy in the grid), different levels of tariff can be calculated and made available for the users/consumers, who can make smarter and more responsible choices. Various large-scale wireless sensor and actuator networks (WSANs) are deployed in a SG to carry information about electric power system generation, transmission, distribution, and home applications for monitoring demand and response tasks.

Currently, there is good momentum on M2M standardization efforts, which aim to achieve interoperability and compatibility in M2M systems independently of the vertical market solutions. Several standardization efforts related to M2M interactions in SGs have been carried out and have contributed to the current state of the art of this area [38-40, 44, 45, 83].

3.2.2 Layered structure of machine-to-machine communications

FIGURE 14 shows the architecture for a SG introduced by the European Telecommunications Standards Institute (ETSI). This architecture is formed by three main layers: the energy layer supporting production, distribution, transmission, and consumption; the control layer; and the service layer [91]. The energy layer includes a large amount of sensors, electricity storage systems, and transmission and distribution systems and corresponds to the machine-to-machine (M2M) device domain in an M2M framework. The control layer connects the energy plane to the service plane and relates to the M2M network domain. Finally, the service layer provides all the SG-related services and corresponds to the M2M application domain in the M2M network architecture. All the architectural components located at the control layer can communicate with each other based on the developed standards, which are shown in TABLE 6 and TABLE 7, defining such M2M interactions. The corresponding interfaces of these components will follow these standards. In other words, the M2M infrastructure allows mapping the developed standards onto corresponding hardware implementation.

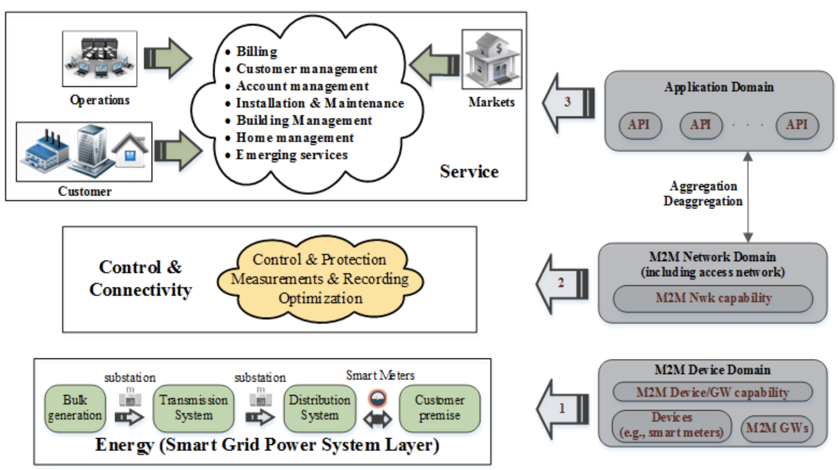

FIGURE 14: The structure of machine-to-machine (M2M) network for smart grids according to the European Telecommunications Standards Institute (ETSI). M2M domains are mapped onto the smart grid main layers.

TABLE 8: M2M wireless technologies and standards implemented in a SG [33, 83].

	802.15.4 (ZigBee/6LoWPAN)	Bluetooth/bluetooth low energy (LE)	802.11 (Wi-Fi)
Max data rate	250 kb/s	3 Mb/s (enhanced) 1 Mb/s (basic or LE)	22 Mb/s (802.11 g) 144 Mb/s (802.11 n)
Indoor range	10–20 m	1, 10, and 100 m classes, 5–15 m (LE)	45 m
Power	Low	medium low (LE)	high
Battery life	Years	days years (LE)	hours
Frequency band	2.4 GHz 868 MHz and 915 MHz	2.4 GHz	2.4 GHz, 3.6 GHz, and 5 GHz
Channel access	CSMA/CA (non-beacon based) or superframe structure (beacon based, non-contention)	frequency hopping or CSMA/CA	CSMA/CA
Applications	smart appliances smart meters lighting control home security office automation	voice smart meters data transfer game control health monitoring computer peripheral	networking between WAN and customer premises (M2M area networks) digital audio/voice

Smart buildings such as offices rely on a set of technology to enhance energy efficiency and user comfort factors as well as for monitoring and safety of the building. The M2M technology and WSANs are used in the building management system for lighting and heating, ventilation, and air conditioning (HVAC). They identify empty offices and then switch off devices such as monitors, lighting, and related IT peripherals and enable security and access systems.

TABLE 8 summarizes major wireless technologies for M2M communications in SGs along with their attributes, advantages, and limitations. It is important to notice that the main requirement of the M2M devices in a home and office environment is their very low power consumption and advantage of mobility. That is because many devices can last years without requiring battery replacement. With the wide range of home/office devices that need to be networked, there is a need to support several different physical layer links.

Among different networking technologies, Ethernet, 802.15.4, Wi-Fi, Bluetooth, power line communications (PLC), and cellular all have a place in the home networking environment. The home M2M network will have to support all the different physical links and protocol stacks through the M2M gateways. The gateways also need to be equipped with corresponding interfaces for gathering information on what processing and energy resources are available in the M2M devices (usually with limited resources) and decide on how to disseminate data to optimize the resources. In general, the gateway capabilities include routing, network address translation (NAT), authentication, resource allocation, and so forth. Other capabilities of the M2M gateway are addressing remote entity management, security, history and data retention, transaction management, interworking proxy, and compensation brokerage. Smart building systems with WSANs are also expected to learn from the building environment and adapt the monitoring and control functions accordingly.

The right side of FIGURE 14 provides a graphical overview of how the three domains of the European Telecommunications Standards Institute (ETSI) M2M reference architecture are mapped onto a SG [33]. The implementation of ETSI M2M communications architecture to SG scenarios is also described in Lu et al. [92]. Based on the layout of the SG's telecommunication network architecture, these domains can be imposed with corresponding parts of this architecture and presented as the overall system (FIGURE 15). FIGURE 15 shows the architecture of this system based on the ICT platform developed under the scope of the European Union (EU) Framework Program 7 (FP7) project called Energy Saving Information Platform (ENERsip) [93]. This project enables electricity consumption, energy costs savings, and proper integration of DERs (distributed energy resources) at the neighborhood level.

As is evident from FIGURE 15, the overall M2M system architecture for SGs is divided into four domains, which represent the main pillars from the ICT perspective [33]. The building domain comprises the physical infrastructures owned by the customers of the power distribution grids, including consumption and generation equipment and the sensor and actuator networks (SANs) to monitor and control them.

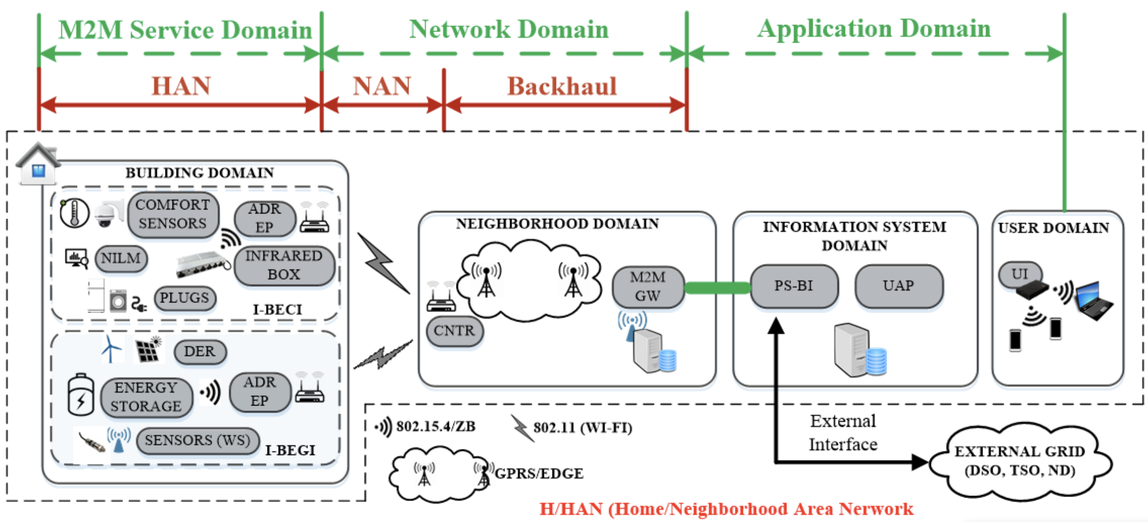

FIGURE 15: Overall system architecture, highlighting the relation with the standardization work.

The user domain (UD) encompasses the means through which the users and the system interact. Within the UD, energy efficiency can be achieved both through automated actions (e.g., switching load regime) and by influencing users' behaviors. Thus, it is crucial to present information to the user in an easily understandable way. Also, the tools provided to the users for making their decisions should be user-friendly. The available applications may run in smartphones, tablets, or even in smart TVs.

The information system domain represents the "brain" of the system from the energy perspective, comprising the logic that allows the optimal use of the available resources at the neighborhood level at any time. Gathering the consumption and generation data of the same location or district at a given moment of time and processing them all together allows reaching global optimizations at the neighborhood level. It is more comprehensive than local optimizations at the household level, as it is the case in state-of-the-art home energy management systems (HEMSs) [50, 94-97]. Additionally, since the users are still allowed to configure a set of parameters and thresholds and they are taken into account when running the optimization algorithms, local optimizations can also be reached.

The neighborhood domain represents the "workforce" of the system and encompasses the core communications infrastructure that carries data and commands back and forward, allowing that everything works correctly. Thus, the information system domain and the user domain are related with IT, whereas the building domain and the neighborhood domain are tightly related with mutual communications.

The consumption and generation infrastructures are named as in-building energy consumption infrastructures (I-BECIs) [98] and in-building energy generation infrastructures (I-BEGIs) [99], respectively. I-BECIs and I-BEGIs may or may not be combined, giving rise to different profiles of customers:

- Consumers: users whose households or buildings are only composed of I-BECIs.
- Producers: users whose infrastructures comprise only I-BEGIs connected to the grid.
- Prosumers [100]: those who own the so-called energy-positive households or buildings, which integrate both I-BECIs and I-BEGIs.

Every I-BECI and I-BEGI is equipped with the so-called automatic demand response (will be further described in chapter 3) end point (ADR-EP). The ADR-EPs work as communications gateways, aggregating and sending consumption or generation data and routing commands to the appropriate device(s). The ADR-EPs communicate directly with their associated concentrator. A given concentrator manages a group of ADR-EPs, forwarding the data coming from them and routing commands to the appropriate ADR-EP(s). Lastly, the M2M gateway has the global picture of the M2M communications infrastructure and works as operation support system (OSS), performing tasks such as network inventory, network components configuration, fault management, or service provisioning, as well as communications gateway to the information system [101].

As FIGURE 15 also illustrates, the communication within I-BECIs and I-BEGIs is based on IEEE standard 802.15.4/Zigbee. The communication between ADR-EPs and concentrators is based on user datagram protocol/Internet protocol (UDP/IP) on top of IEEE 802.11; and the communication between the concentrators and the M2M gateway is based on transmission control protocol (TCP/IP) on top of general packet radio service (GPRS). López et al. (2011) [101] explain why these communications technologies are chosen.

The M2M communications architecture proposed in López et al. (2014) [33] can be mapped onto the communications technologies of interoperability architectural perspectives (CT-IAP) of the overall IEEE 2030 smart grid interoperability reference model (SGIRM), as shown in FIGURE 15 in the continuous line of red arrows. The I-BECIs and the I-BEGIs represent the HANs, and the ADR-EP provides the functionality of the energy service interface (ESI); the communications segment comprising the ADR-EPs and the concentrators represents the NAN; and the communications segment composed by the concentrators and the M2M gateway represents the backhaul.

In a dashed line, FIGURE 15 also shows the relationship between the M2M domains defined by ETSI [91]. The SANs within the I-BECI and I-BEGI can be seen as capillary networks at the customer domain. The M2M communications architecture can be shown in two main sites (FIGURE 16) [92]: M2M core and M2M devices are connected through corresponding communication networks. Each site consists of parts that belong to SG conceptual model [39, 40].

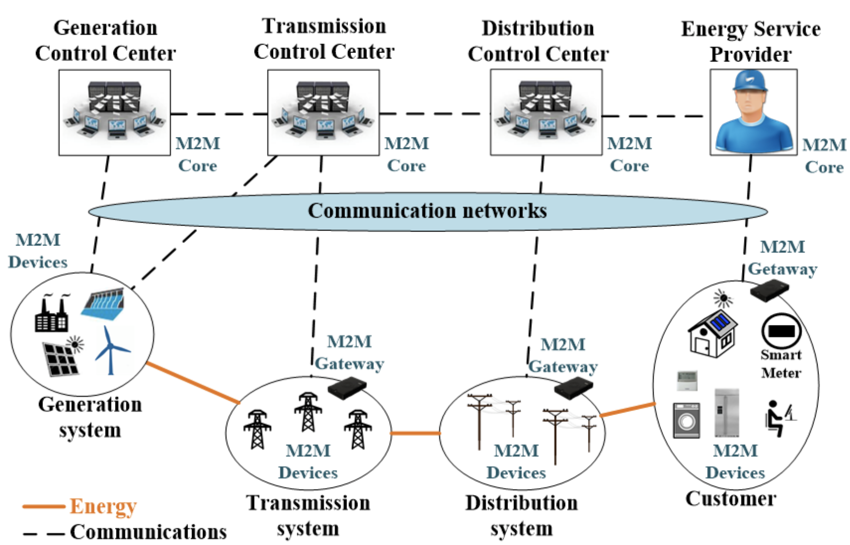

FIGURE 16: Mapping of the proposed M2M communications architecture onto the European Telecommunications Standards Institute (ETSI) M2M architecture applied to the Smart Grid.

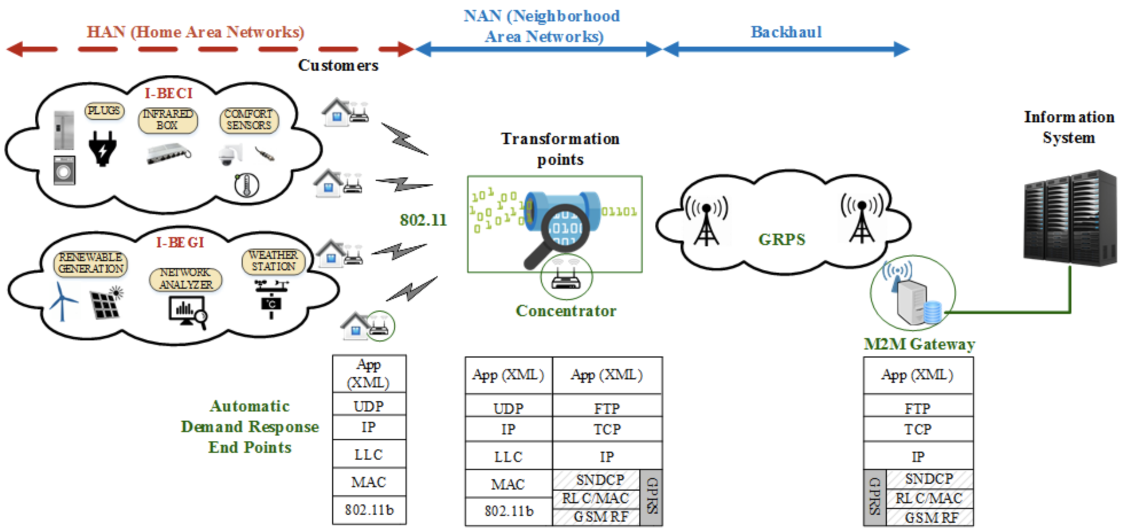

FIGURE 17: Mapping of the proposed M2M communications architecture onto the power distribution infrastructure.

FIGURE 17 shows a mapping of the proposed M2M communications architecture onto the power distribution infrastructure [33]. In this figure, the automatic demand response end points (ADR-EP) are associated to the customers and the concentrators, which are also associated to the transformation points or feeders.

The M2M gateway is logically associated to the substation that manages the target neighborhood. However, using GPRS as backhaul technology allows the M2M gateway to be physically located at the substation or the data centers of the entity operating the platform: distributed system operator, retail electric provider, aggregator [33, 47, 91, 92].

The significance of M2M communication in SGs follows from the numerous benefits that it brings. First, real-time M2M communication establishes a close interaction between energy users and the ESPs, which in turn allows to reduce the retail energy price and improve the efficiency of energy generation, transmission, and distribution [19, 20, 67, 76, 77]. Advanced data analytics enabled by M2M communication in combination with IoT sensing is the other major benefit. The main applications of this benefit are proactive decision-making (e.g., demand response management by ESP) and future electricity price forecasting in SGs [102-109]. Additionally, the self-healing feature of SGs enabled by implementation of M2M communications increases the grid's reliability and improves its resiliency to failures [110].

3.3 Application of Internet of Things in smart grids

Although the definition of IoT is still evolving, it was attributed a major role in providing comprehensive access to services and data supplied by large number of diverse devices in an interoperable way [33, 91, 111, 112]. As mentioned by the IoT European Research Cluster (IERC), IoT is "a dynamic global network infrastructure with self-configuring capabilities based on standard and interoperable communication protocols, where physical and virtual "things" have identities, physical attributes, and virtual personalities and use intelligent interfaces, and are seamlessly integrated into the information network [113, 114]." Seeking applications in different areas of SGs' infrastructure: smart metering, generation, transmission, distribution etc., IoT play a key role in the current development of SGs [78]. This development is accelerated by recent improvements of main features of IoT devices: storage capacity, processing power, miniaturization, and the self-determining capability to "connect and sense" [115-119].

An Internet of things (IoT) implementation in Smart Grids (SGs) mainly consists of physical components acquiring information from metering/sensing devices, such as intelligent sensors, actuators, etc. and sending it to a resultant data concentrator (e.g., aggregator with corresponding gateways) [116-118, 120]. This data concentrator in turn modifies information to suit the required Internet protocols (e.g., TCP/IP) for web services or cloud computing platforms, which further processes it and takes the required actions [116-119]. Within a SG, such computing platforms are located at the Energy Service Providers' (ESP) sites. Those sites are connected with the corresponding Aggregation layer through an underlying Network layer [116-119]. The overall process of data handling presented by IoT processing layers can be mapped to the telecom infrastructure of SGs as illustrated in FIGURE 18 [41]. A specific realization of these IoT layers in the infrastructure of a particular SG depends on the underlying architecture of the corresponding power system (scale, density of energy loads, etc.).

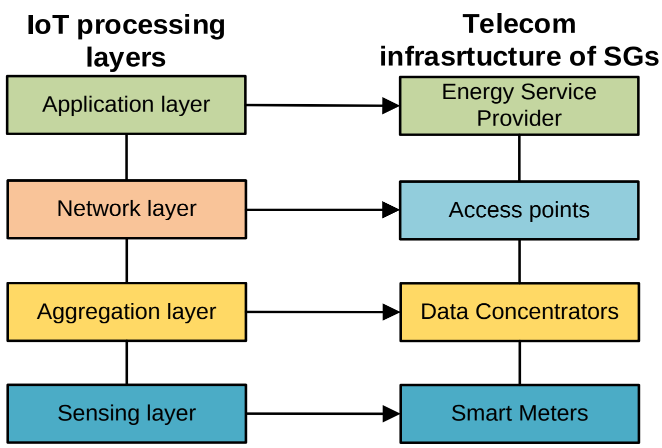

FIGURE 18: A relation between IoT processing layers and telecom infrastructure of SGs. Sensing, aggregation, network, and application layers are mapped on corresponding nodes of telecom infrastructure of SGs [41].

Physical devices used for IoT based networks follow multiple communication standards based on corresponding limitations of information and telecommunication technologies (required bandwidth and reach) and the architecture of a certain power system. For instance, a lower radio frequency (RF) with a Sub-1 GHz mesh network and the IEEE 802.15.4 2.4 GHz ZigBee standards are the most popular in the US. In the UK and Japan, implementations of Sub-1 GHz RF or power line carrier (PLC) solutions with a longer reach are evaluated as better options [121]. Smart metering devices, are capable of providing data formatted in ZigBee, comma-separated values (CSV) and java-script object notation (JSON) [122]. Several solutions with 6LoWPAN [107], ZigBee-IP [108], and Wireless Smart Utility Network (WI-SUN) along with IEEE 802.11g are utilized for monitoring of energy consumption [109, 122].

The described IoT standards were implemented in several hardware platforms: SmartEnergy, which manages assets dynamically and reduces energy costs and outages [123]; and Techno-Pole, which predicts energy behavior based on data incentive solution [122], etc. Besides, the communication standards for IoT implementation in SGs are defined by a scale of an underlying power system. It is common for large scale power systems to utilize telecom standards with various bandwidth and coverage. For instance, GPRS, 3G, and Power 4G standards were utilized at Henan Hebi, the first largescale demonstration project of IoT's implementation in SGs [124]. Additionally, expansion of IoT in SGs is related to integration of its communication link in an electrical network, which in turn is subject to supported transmission and reception data rates, network topology, layered architecture, routing delays and onboard processing speeds [125].

The IoT system has typically evolved with distinguished solutions, in which every component is designed for a particular application context [126]. Hence, standardizations in technology stack, communication protocols, and data sources along with integration feasibility are required [36]. IPv4 is the most widely used version of a protocol at the Network layer of IoT processing scheme (FIGURE 18). The most recent version, IPv6, has several advantages with respect to IPv4 [78]. However, not all of currently utilized SG technologies support IPv6 protocol. Due to this reason, a deep analysis of communication network infrastructure is needed before defining IPv6 protocol for network addressing of the loads and other devices connected to a SG by IoT [78]. Additionally, a secure communication interface would be required for communication between TCP/IP stack supported devices with non TCP/IP stack supported devices (e.g., protocols as ZigBee, HART) [79]. This requirement is also applicable in the case of devices supporting same protocol stacks but different feature capabilities, such as one having Datagram Transport Layer Security with/without certificate support [79].

With the demand to analyze a continuously growing amount of data collected in SGs, new and optimized software needs to be implemented [78, 81, 85, 127]. Thus, requiring the software infrastructure to be modular and scalable. Additionally, large volume of information exchanges in an IoT-enabled SGs would require systems capable of computing and storing data in real-time. Due to this reason, the corresponding data storage devices need to be selected for IoT implementation in SGs. At the same time, such implementation will bring an additional cost to the manufacturing, deployment, maintenance of SG-focused IoT devices [128].

Thus, it is evident that a single wireless solution might not be the best choice, but its selection can depend on the existing telecom infrastructure, type of grid, cost of transition or deployment, requirements of application in terms of wireless connectivity options, power constraints, and bandwidth requirements [121]. Besides, aspects over the air (OTA) programming updates can affect scalability, maintainability, security, and interoperability, which will define the choice of a wireless solution. An absence of a unique solution for IoT implementation in Smart Grids (SGs) is evident. Based on existing infrastructures and types of SGs, their scale and density of their energy users, various physical designs and computational platforms are currently utilized to accomplish the goal of IoT performance in SGs.

According to “Architectural Considerations in Smart Object Networking” [129], four models of IOT communication are currently considered [129, 130]: Device to Device, Device to Cloud, Device to Gateway, and Back-End Data Sharing Pattern. The implementation of these models in SGs is presented in TABLE 9 [41].

TABLE 9: IoT models in Smart Grids

Model	Implementation example
Device to Device	An IoT sensor with another one
Device to Cloud	An IoT sensor with the ESP
Device to Gateway	An IoT sensor with the access point
Back-End Data Sharing Pattern	The ESP with another one

Several software packages were developed to accommodate the transition from traditional to smart energy grids. These packages are mainly represented by distribution management system (DMS), geographic information systems (GIS), outage management systems (OMS), customer information systems (CIS), and supervisory control and data acquisition system (SCADA) [110, 131, 132]. Ubiquitous sensing, data analytics, and an information presentation platforms are required for communicating between numerous applications designed during further development of SGs [133]. It was shown that cloud computing platforms can be successfully used for energy management, security of grid utilities and consumers, as well as communication and information management within a SG [78, 134]. These platforms can be classified based on their models, architecture and services provided [134]. Utilization of computing platforms, such as Aneka [133], Fog Computing [78], XENDEE [22], are beneficial with the dynamically changing nature of IoT environment. Additionally, XENDEE provides a cloud-computing platform for smart micro-grid project management and power system analysis [22]. Development of diverse yet user-friendly platforms can help reduce the time, effort, and costs associated with SG deployment and management.

The implemented computing platforms enable various web services for monitoring, management, and control of the SG infrastructure: Energy Management Systems (EMS), GreenBus Microgrid Solutions, Advanced Microgrid Solutions, etc. [11, 20, 107]. These services vary in terms of the cost, ability to integrate with third-party solutions, digital infrastructure (e.g., databases), and the scope of utilization/ customization (of existing versus new infrastructure). It is important to notice that integration of IoT with such a large number of web-services and protocols is a key challenge for smooth IoT’s transitioning to a SG model [14, 15, 115, 118, 135, 136]. Considering application specific requirements and constrained resources, protocols for IoT in general can be classified into the following broad categories: application protocols, service discovery protocols, infrastructure protocols, and other influential protocols [137]. Being the most relevant to the current chapter, IoT application protocols utilized in SGs are mainly presented by Constrained Application Protocol (CoAP), Message Queue Telemetry Transport (MQTT), Advanced Message Queuing Protocol (AMQP), Extensible Messaging and Presence Protocol (XMPP) with Data Distribution Service (DDS) [137]. These protocols can be compared using following aspects: Quality of Service (QoS), Representational State Transfer (REST) compliant services, header size, Transport Layer dependency (TCP/UDP), and offered security, which can be divided in Transport Layer Security (TLS) / Datagram TLS, messaging pattern, and request/response functionality [137]. Although a single implementation of IoT protocols may not be available, certain solutions show efficient performance in specific scenarios and environments [137].

IoT devices seek applications in various parts of SGs, which include the scope of customer interactions, energy generation and distribution, smart metering, grid management and maintenance [41]. In Home Area Networks (HANs), Building and Industrial Automation Systems (BASs and IASs), IoT technologies are used to attain an automated energy management, its efficient usage, and comfort functionality. These applications include studying patterns of energy usage and controlling the loads accordingly [78, 100]. Deployment of IoT in energy harvesting farms (e.g., wind, solar, etc.) and energy storage systems improved energy forecasting by achieving a balance between energy generation, storage, and consumption [14, 15]. Additionally, IoT ’s implementation was advantageous for energy generation and distribution in autonomously powered islands in case of failures and blackouts, for readjustment of excitation controls and load shedding, system restoration and aspects of self-healing [78, 113]. An IoT based online system controlling power transmission lines presented in [136] describe its major monitoring parameters: transmission tower leaning, conductor galloping, wind deviation and vibrations, micro- meteorology, conductor icing, and temperature control. Using such online control systems, these parameters are monitored in real-time and subjected to further analysis, which in turn would be used to maintain a reliable operation of power transmission [136]. Thus, IoT play an important functional role in generation, transmission, and distribution domains of SGs.

IoT's usage in smart energy metering, energy management, and maintenance are the other major areas of its implementation in SGs. Using IoT and cloud-based systems meters or data concentrators can send data to Energy Service Providers (ESP) or cloud services using suitable interfaces. Large amount of data can be monitored with IoT utilization in SGs on a frequent basis. Therefore, it will in turn increase the probability of required repairs that can be initiated in an event of damage or failures in a timely manner [21, 78, 138]. For example, usage of information about energy system parameters, such as the dynamic heat capacity, line-icing, galloping of power lines, impact of wind etc. can enable earlier fault detection and repairs [78, 136]. Various leading providers of industrial IoT smart meters, such as MOXA [11], Sierra wireless [21], Itron [138], etc., are already leading the forefront of smart metering. In addition to the increased amount of data, IoT implementation in smart metering systems brings another level of intelligence that enhances the functionality of Advanced Metering Infrastructure (AMI), communication network supporting smart metering [14, 15], and its scalability [139]. IoT can enable efficient asset management by enhanced monitoring of status and operation of SG assets [78]. Therefore, maintenance of existing grid assets and planning of grid expansion can be dealt with in a better manner using data obtained from IoT.

Deep and extensive implementations of IoT in SGs is being established through Machine-to-Machine (M2M) communication in real-time and close interaction between energy users and the ESPs. This interaction can in turn reduce the retail energy price and improve the efficiency of distribution and generation by renewable and traditional energy sources [19, 20, 67, 76, 77].

Predictive analytics performed on real-time data obtained from IoT makes SGs proactive by aiding in the effective maintenance, precise generation, load balancing, and efficiency improvement of an energy grid. Using data analytics, ESPs can make quick decisions and better adapt to supply and demand [102]. Specifically, data analytics is widely and extensively used for future electricity price forecasting in SGs [103-106]. Various statistical and mathematical tools are adapted for data analytics: artificial neural networks, support vector machines, along with engineering and statistical methods [94, 140-142]. Very often, these tools are accompanied with the corresponding analysis methods [143-149]. Both of these methods will be described on more details in chapter 3.

The self-healing ability of a SG to quickly repair itself in the event of any external or internal disturbances is significantly improved by implementation of IoT sensors [78, 113, 136]. In an event of destabilization, intelligent devices based on real-time data distribution can isolate faults and achieve global optimization and reorganization to resume operation [20, 150]. In case of SGs, such ability makes then able to resume operation after attacks, blackouts and network failures.

The Internet of things (IoT) is a rapidly evolving technology capable of transforming numerous areas of our lives. Smart Grid (SG) is one of such areas, which has an immense potential of development, following the advances in IoT technology. Each domain of the Smart Grid conceptual model (FIGURE 2) is characterized by a tight integration of flexible and secure communication networks [14, 15, 39, 40]. In addition to these networks, a large number of sensors and actuators are required to implement novel energy management techniques within a Smart Grid (SG). The entire monitoring and control infrastructure of a SG is deployed by means of M2M communications and the Internet of Things (IoT) paradigm. Applications of IoT in SGs are described for several structural and functional parts of SGs: Customer Interactions, Generation, Transmission, Distribution, Smart Metering, Grid Maintenance and Management. Besides, IoT friendly AMI supported by M2M communications architecture are key to achieve such goals [107-109].

Providing numerous advantages, IoT based SGs also introduce new security and privacy challenges on the customer, communication, and grid domains information [74, 77]. Various aspects of users' identification, authorization, and access control are concerning in cyber security of IoT systems, such as 'Fog Computing', and need to be addressed [74, 77, 78]. IoT based SGs are also subject to security issues based on impersonation, data-tampering, malicious-software, Denial of Service (DoS), and Cyber-attacks [79]. Various security practices and approaches, such as anti-virus, firewalls, intrusion prevention systems, network security design, defense-in-depth, and system hardening are currently incorporated to protect SGs [151]. Usage of approaches based on security keys, cryptographic algorithms, and hidden IDs are used to protect privacy while integrating embedded IoT devices to cloud services [152].

3.4 Application of hybrid optical networks for smart grids

It was shown in chapter 1 that each domain of the Smart Grid (SG) conceptual model (FIGURE 2) is characterized by a tight integration of flexible and secure telecommunication networks [14, 15, 39, 40], which are required to be reliable, scalable, and cost-efficient [69, 153]. A continuous and uninterrupted information flow is an essential requirement for SG operation, e.g., an unprotected telecommunication network is not acceptable for control of a vital energy service. Furthermore, different degrees of resilience are required in order to accommodate different customer domains and user profiles in the same network. Scalability and flexible architecture of telecommunication network for SG is crucial for integration of emerging energy services such as charging stations for electric vehicles [6, 27, 76] and drones [32, 75], wireless charging [32, 75], etc.

In a hybrid passive optical network (HPON), PON is usually considered as the wide area network (WAN). Neighborhood and home area networks (NANs and HANs) of HPON are presented by hybrid (with PON) communication media: wireless, cellular, copper cabling, etc. [16], [22], and [37]. The scheme in FIGURE 19 shows a part of the general HPON topology for a SG, where the passive optical network (PON) is utilized as a WAN. Wireless, microwave, power line connections (PLC), and free space optics (FSO) communication technologies are used as NANs and HANs of the presented HPON. Utilization of 4G/5G [15] networks in HPON technology can provide a broadband connection to the end users and become very promising in cost-aware telecommunication network design for SGs [22], [37].

Applications of HPONs in telecom media of SGs have been analyzed in [16], [22], and [37]. Based on this analysis, HPONs can be advantageously utilized as WANs for SGs' certain circumstances.

Since HPONs have broader transmission bandwidth than wireless networks and other protocols implemented in SGs [14, 15], they are able to provide a large number of clients per distribution line (see FIGURE 19) remaining scalable for future upgrades [24, 39, 137]. Besides, taking into account low losses in fiber distribution systems ($\leq$ 0.2 dB/km), HPONs can perform and maintain a broadband (over 100 Gb/s per client) connection to the remote devices located at distances of more than 40 km from the central office [54]. It is well established now that HPONs have high cost-efficiency [154, 155], which can be achieved using only passive components in transmission paths and, on the other hand, by reducing the amount of components at the distribution control center (DCC) and optical network unit (ONU) modules in users' domains based on hybrid technology [69, 156]. The low cost of passive components [153, 157] and the significant reduction of spectral channels in the DCC and ONU modules with hybrid technology [69, 156] in the transmission path provide the other key advantage of implementation of HPONs as telecommunication networks for SGs. The flexibility of protection schemes for HPONs is another advantage for their implementation [54, 156, 158].

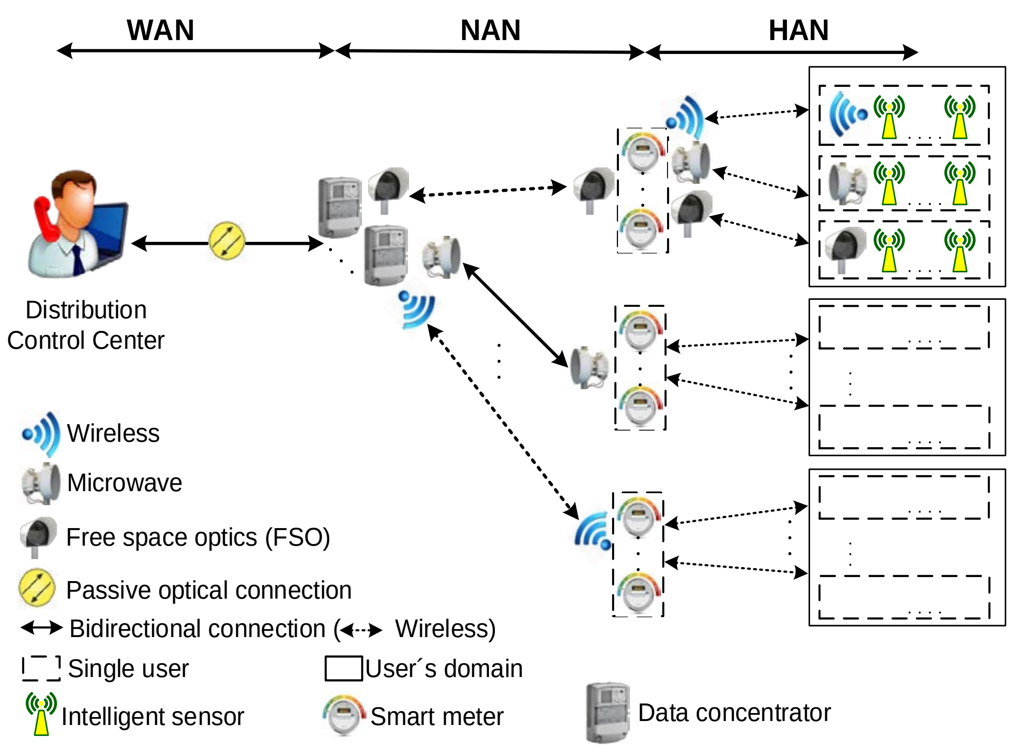

FIGURE 19: Schematic topology of a hybrid passive optical network (HPON) for an advanced metering infrastructure (AMI) of SG telecom network. HPON is implemented as a backbone network. Wireless, microwave, and free space optics technologies are considered for distribution and access networks.

Since WAN carries the largest amount of information in SG telecommunication network (see section 2.1), it is considered to be represented by passive optical connection (see FIGURE 19). As a high amount of information carried by this connection, which can be further expanded into a passive optical network (PON), it is crucially important to provide reliable protection schemes for it [22]. General architecture of PON is shown at FIGURE 20-a. Optical line terminal (OLT) and optical network units (ONUs) are the end points and the only active elements of this scheme. The communication media between these points is presented by optical fiber interconnections: feeder fiber (FF), distribution and last mile fibers (DFs and LMFs respectively) and remote nodes of first and second levels (RN1 and RN2), which are represented by power splitters (PSs) and array waveguide gratings (AWGs) (FIGURE 20-a). The total capacity of such PON architecture can be more than 1000 ONUs, which are further connected to the corresponding entry points of NAN using hybrid with PON telecommunication technologies (see FIGURE 19). Different types of protection schemes for PON architecture are presented at FIGURE 20-b,c [22].

A scheme with protection up to remote node 1 (RN1) of PON (FIGURE 20-b) implies the protection of shared equipment and fiber-paths decreasing the risk of service interruption for all users connected to the WAN. Such protection is achieved by adding the second optical line terminal (OLT) (or optical transceiver) included in central access node (CAN) of PON located at the DCC (see FIGURE 19) and an additional optical feeder fiber (FF). The main goal of the protection up to RN1 is to support PON components with higher failure rate and impact resulting in connection unavailability. Since OLT transfers the largest amount of data in SG network on one side and optical FFs covering long distances in PON on the other side, the corresponding failure impact of these components will be high [22]. It was shown that implementation of protection up to RN1 in PON reduces connection unavailability to 10^{-5} compared to unprotected case by 5% investment cost increase [154, 155].

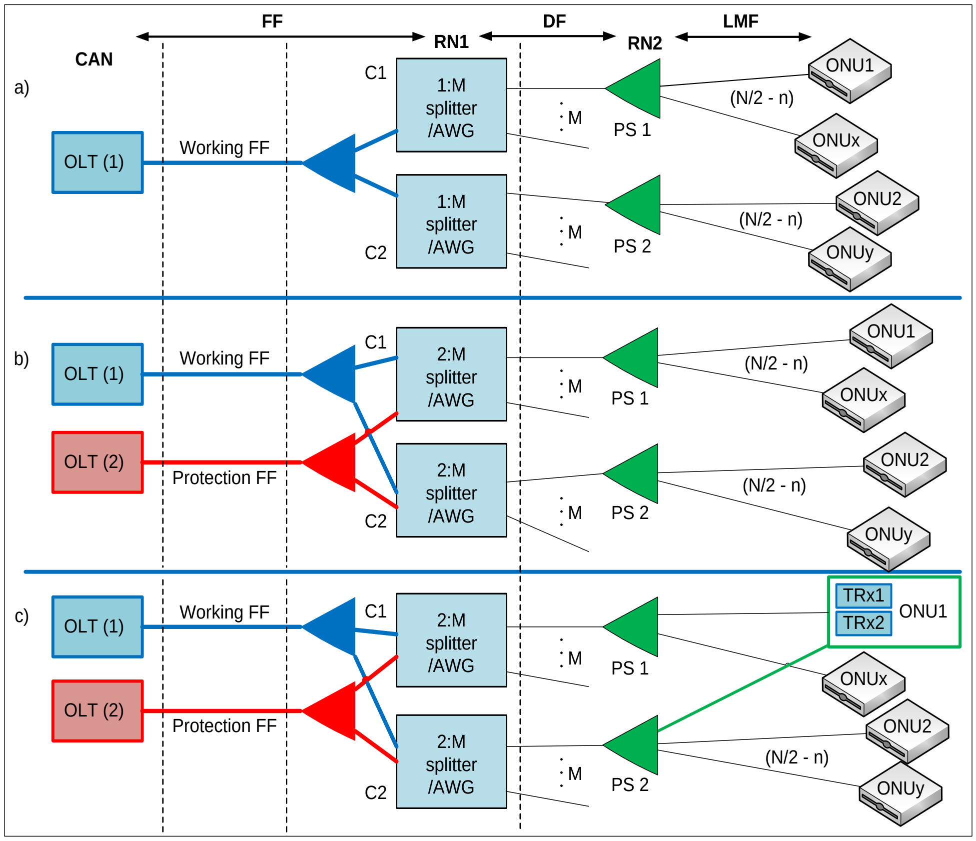

FIGURE 20: PON architecture: (a) without protection; (b) with protection up to RN1 for all connected ONUs; (c) E-to-E protection for some selected ONUs [153].

The end-to-end (E-to-E) protection scheme shown at FIGURE 20-c offers protection of the entire telecommunication path in PON [153]. Similar to protection up to RN1 scheme, E-to-E protection scheme duplicates OLT and FF as components with high failure impact. Additionally, E-to-E protection supports PON components with lower failure impact, such as DF, RN2, LMF, and ONU, including the additional links between RN2 and ONUs. Therefore, such protection further reduces connection unavailability and can be implemented for critical SG applications with highest reliability requirements [22]. At the same time, the implementation cost of E-to-E protection scheme is higher than it is for protection up to RN1 scheme. Therefore, E-to-E protection scheme will be the most cost-efficient for areas with high density of users [153, 157].

The Radio over fiber (RoF) refers to a technology whereby light is modulated by radio signals and transmitted over an optical fiber link to facilitate wireless access [159]. This technology became promising for reduction of delays in a broadband data transmission of SG telecommunication network [159-161]. A part of SG telecommunication architecture based on the RoF technology with a two-tier hierarchical structure for a residential customer domain is considered at FIGURE 21 as an example [139]. This architecture refers to two parts of SG communication network: the WAN and NANs, which correspond to clusters 1 and 2 (higher and lower) of RoF architecture [160]. Since WANs are supported by optical fiber links, this architecture provides the broadband data transmission. Multiple HANs with their IoT sensors (see section 2.1) have bidirectional connection with their data concentration stations (DCS) through corresponding NANs. Within RoF network architecture, these DCSs are located at radio access units (RAUs). The DCSs in their turn connected bi-directionally with the base station located at the ESP side and controlled through corresponding WAN.

In RoF technology [139, 160, 161], DCSs perform data aggregation and transmission in a manner similar to data concentrators in a conventional telecommunication architecture of SGs [44, 46, 54, 87, 88]. A part of SG telecommunication architecture based on RoF technology is shown at FIGURE 21. Each base station (BS) of this architecture is connected to SG distribution control center (DCC) located at the ESP side (see FIGURE 19) through a fiber or, in some cases, through a point-to-point wireless connection with high capacity [139]. As it displayed in FIGURE 21, a two-tier hierarchical clustered structure of RoF obtained by combining WANs and NANs of two sectors of SG (e.g., based on geographical location or user domain) can support resource allocation over a range of coverage areas. The main advantages of the presented RoF architecture (see FIGURE 21) are flexible access to various locations supported by RAUs and extended coverage between DCSs connected by optical fiber links. Such flexibility of access allows SG's sensors (e.g., located at the users' side) to establish connection with the DCC using less number of nodes and, therefore, reducing the transmission delays [139, 160]. At the same time, the clustered structure excludes broadcast downstream for all users reducing the amount of traffic in WANs of SGs.

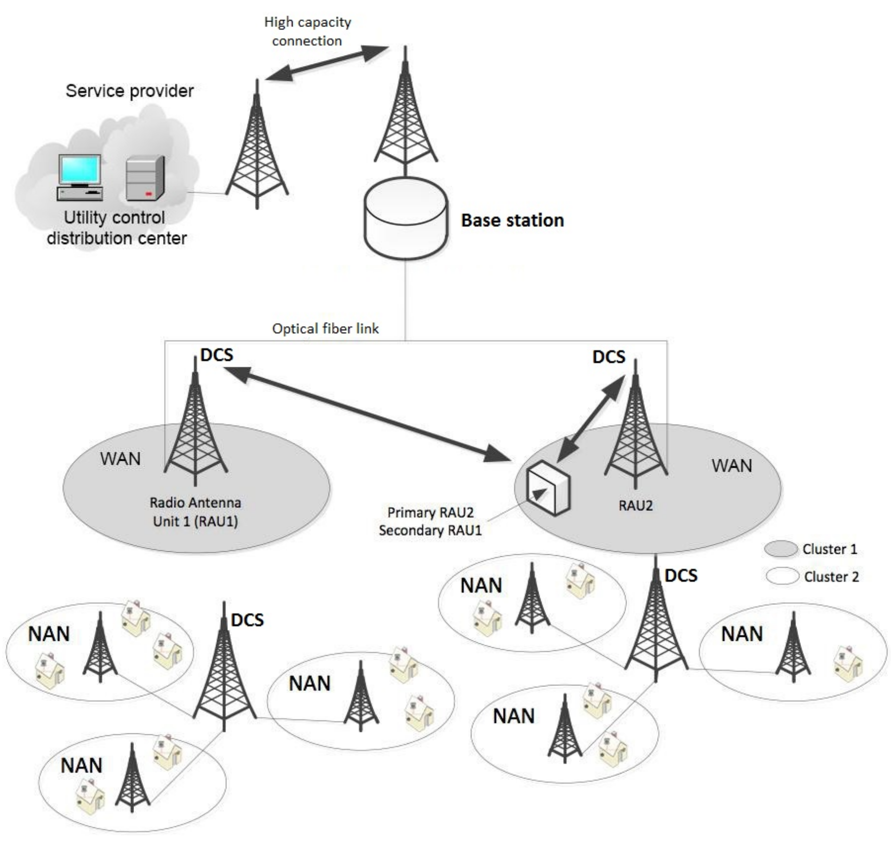

FIGURE 21: A part of SG telecommunication architecture based on the RoF technology with a two-tier hierarchical structure. The residential domain of SG is considered [139].

Previous studies have considered the other advantages of RoF communications such as energy efficiency [159] and diversity gain [159, 161] for conventional wireless networks. Implementation of RoF networks with cognitive radio technology will increase the scalability and flexibility of such networks by utilization of temporally unoccupied spectral band, which is referred to as ‘spectrum-hole’ or ‘white space’ [159, 161]. If such spectral band is being occupied by a licensed user, the cognitive radio moves to another spectrum-hole or stays in the same band, altering its transmission power level or modulation scheme to avoid interference [159, 161].

3.5 Summary

In this chapter, an application of hybrid telecommunication networks for smart grids (SGs) have been described from various perspectives: telecom technologies and protocols, intelligent machine-to-machine communications (M2M), Internet of Things, and hybrid optical networks. Most of telecommunication technologies implemented in SGs are wireless and required to meet specific requirement for quality of service (QoS), interoperability, scalability, security and privacy. described with a M2M communications in SGs have been reviewed in the original manuscript submitted within the corresponding book chapter. These requirements are different for various applications of telecom networks in SGs. The lack of a protocol that can satisfy the heterogeneous requirements of various communication types in a SG has resulted in a highly fragmented protocol stack in SG telecommunication systems. M2M communications in SGs are described using their reference architecture and layered structure, which is utilized to show the mapping of layers of M2M communications structure on the domains of SG. Applications of IoT in SGs are described for several structural and functional parts of SGs: Customer Interactions, Generation, Transmission, Distribution, Smart Metering, Grid Maintenance and Management. Mapping of IoT processing layers on telecom infrastructure of SG has been presented introducing four models of IoT in SGs. Application of hybrid optical networks in SGs is a special focus of this chapter. It allows to obtain a broadband access to remote sensors and other connected devices of SGs allowing to maintain scalability and flexibility. In addition to that, hybrid optical networks can support implementation of various telecom technologies at SG access network. The ultimate choice of communication technology for access network (wireless, microwave, free space optics, etc.) is usually based on the specific location of energy users, their requirements and density. Radio over Fiber technology can be advantageously utilized for overall reduction of transmission delay and amount of traffic in wide area networks of SGs.

CHAPTER 4: DYNAMIC ENERGY DISTRIBUTION AND MANAGEMENT

4.1 Dynamic demand estimation enabled by IoT sensing

Deployed at customer domains of a SG (see section 2.1), home area networks (HANs) provide a convenient capability for direct energy demand estimation through monitoring and control of various intelligent sensing devices (see sections 2.2 and 2.3). In most of cases, such energy demand estimation (e.g., from ESP side) can be performed through the usage of smart meter's (SM's) or data concentrator's interface by means of Meter Data Management System (MDMS) application (see section 2.1). An interconnection of intelligent sensing devices, SMs, and data concentrators forms a general advanced metering infrastructure (AMI) of a SG (FIGURE 12). Energy demand management is one of the main functions of AMI (FIGURE 10).

Among all sensors (phasor measurement units, intelligent electronic devices, etc.) implemented in existing AMI, an Internet of Things (IoT) based sensors integrated with energy loads or externally connected to them play an important role in energy demand estimation and management, e.g., through dynamic scheduling of energy loads [18-20]. Following the idea described in studies [14, 15], when electric loads are turned on, IoT sensors connected to them will send "energy request" signals containing the other loads' parameters required to process each "energy request". These parameters can include loads' running time, their regime or other settings such as energy load profile, i.e., variation of load's power consumption during its operation time [17, 162]. It can also be considered to store energy consumption profiles of certain appliances and equipment at data concentrators level [16]. After obtaining energy pricing information from markets domain (FIGURE 2), "energy request" signals received by DCC can be processed and corresponding loads can be scheduled sequentially or based on chosen service requirements and constraints [14, 15]. This information will be transmitted through and shared with corresponding SMs and data concentrators of the certain user domain (FIGURE 12).

The described process of energy loads scheduling can be performed dynamically, which in turn will allow the ESP to estimate energy consumption needs in real-time and transfer them to energy generation side [14, 15, 37]. It should be noticed that the required accuracy of energy consumption estimation can be achieved by the corresponding choice of energy loads and as a trade-off with efficiency of IoT sensing network [17]. In addition to that, the energy consumption estimation can be performed at a finer granularity level by decreasing the sampling interval of energy load profile (see section 3.1.3 for details). This enhancement will allow the ESP to dynamically estimate the energy consumption requirements of its users more accurately and run SGs more efficiently [14, 15, 37]. At SGs' telecommunication network level, such dynamic estimation of energy consumption is based on a continuous bidirectional data flow between the ESP and IoT sensors connected to energy loads at customer domains. Hence, the corresponding requirements for bit-rate and bandwidth of SG telecommunication channels will be increased. Therefore, application of hybrid optical networks will play an important role in dynamic energy estimation and dynamic demand side management.

4.2 Dynamic demand response in Smart Grids

As noted earlier, one of the main functions of SGs is an efficient energy distribution, which is widely implemented in Demand-side management (DSM), which was first proposed by the American Electric Power Research Institute (EPRI) in 1980s [163]. Developed afterwards DSM programs enable ESPs and utility companies to manage the user-side electrical loads and energy consumers to voluntarily lower their demand for electricity [164]. Alternative to increase of conventional electrical power generation, DSM programs compensate electrical energy users for lowering their energy consumption [14, 50, 164]. Present DSM is a set of flexible and interrelated programs that provides customers a substantial role in reducing their general electricity usage and shifting it from on-peak to off-peak times fostering higher efficiency and operational sustainability of SGs [14, 50, 164].

As an important form of DSM, demand response (DR) refers to market-based behavior of energy consumers in changing their original electricity consumption patterns in response to market price signals or incentives. DR are voluntary programs that compensate end-users of energy for reducing their electricity utilization or shifting it from on-peak to off-peak periods [10, 165-167]. Various time-based rates of energy pricing (e.g., critical peak pricing, variable peak pricing, real time pricing, and critical peak rebates) and incentive payments are the most common compensations provided for energy users participating in DR programs generally categorizing them in incentive-based and price-based [14, 50]. On one side, DR provides an opportunity for end-users of energy to play a significant role in energy distribution within SGs [37, 166]. On the other side, demand response programs are used by ESPs and electric system planners for balancing supply and demand, lower the cost of electricity in wholesale markets, and in turn in retail [168]. Besides, DR programs include direct load control providing, for example, the ability for ESPs to cycle HVACs and water heaters on and off during periods of peak demand in exchange for a financial incentive and lower electric bills [165, 168-170].

In traditional DR programs energy consumption estimation is done a day ahead of the day when the corresponding action is to be performed [171]. However, SGs are currently transitioning towards dynamic demand response (DDR), in which ESPs need to estimate energy consumption a few hours in advance due to dynamically changing conditions of the grid [10, 14, 50]. In a more detailed approach, energy distribution within a fraction of an hour can be considered [14, 50]. Dynamic Demand Response (DDR) can be defined as a "process of balancing supply and demand in real-time and adapting to dynamically changing conditions by automating and transforming the demand response planning process" [172]. There are several factors that drive a transition towards DDR: integration of renewable energy sources, which have supply instability due to their uncertain nature; need to limit energy production at time periods traditionally considered as non-peak periods (e.g., weekends, hot summer afternoons, etc.); spikes in consumption at arbitrary times introduced by charging of electric vehicles (see chapter 4 for details) [26, 171, 173, 174]. Additionally, DR programs have been focused at large industrial and commercial customers [171], who are expected to contribute in a large-sized energy consumption curtailment. However, the participation of small residential customers in demand side management is increasing [9, 171, 175, 176]. The energy demand of such customers is usually easier to manage, e.g., by shifting or "shaving", as compared to the energy loads of commercial entities and industrial factories [9, 14, 50]. DR models well-performing for large commercial customers with smaller energy consumption variability over time are less efficient for small residential customers, whose energy consumption pattern fluctuates significantly [14, 50]. However, it should be noticed that consumption prediction for small customers is quite challenging at high temporal granularity [177, 178].

Although the existing work has focused extensively on improving consumption prediction models for large energy users [9, 175, 177, 179, 180], there has been significantly less research studies on a DSM for residential customers. Specifically, DSM of residential customers implemented through DDR with a short-term energy consumption estimation has been originally considered in this research. In addition to that, such DDR has been introduced in combination with a PEVs' charging station functionality of a SG. Such combined functionality of short-term energy distribution within a certain customer domain and charging of PEVs (e.g., by an autonomous charging station through online scheduling scheme) creates so-called "dual-purpose" SG. While short-term energy distribution for residential customers is considered in this chapter, the next one is devoted to the operation of SG as a charging station.

4.3 Dynamic load scheduling

4.3.1 Optimization approaches and models

The proportion of residential energy consumption has reached around 30–40% of the total energy consumption in the world and keeps increasing with the growth of population and residents' disposable income [22, 181, 182]. It is known that the current development of smart home enables scheduling of household loads [130, 183, 184]. Such scheduling is utilized in DSM to achieve power supply and demand balance by changing the curve shape of the total load profile of a household [11, 18-21, 138]. Besides, it leads to energy efficiency improvement and slows down the unnecessary enlargement of SGs [14, 50, 185]. Thus, optimization of household load scheduling has excessive practical significance for DSM.

Various models have been proposed to optimize scheduling of household loads [12, 167, 186-188]. Each model differs in its choice of optimization objective such as total energy cost, operation delay, level of comfort, etc.; approach such as analytical framework or discrete-event simulation; and technique such as simulation optimization, mixed integer programming, and stochastic.

In reference [189], a method of dividing demands into 'essential' and 'flexible', was utilized for energy consumption management. According to this approach, 'flexible demands' were further categorized into delay-sensitive and delay-tolerant based on historically given probabilities. In this study, a problem was expressed to minimize the total energy cost and the operation delay for flexible demands by obtaining optimum energy management decisions [189]. In [190], the optimal energy management method considering comfortable lifestyle was developed for residential buildings using multi-objective mixed integer nonlinear programming model. A "thermal comfort zone" algorithm was used to ensure an optimal load scheduling. The goal of the optimization problem formulated in [190] was to minimize the cost of the energy obtained from the 'external grid' defined by traditional energy sources. In study [191], the innovative concept of electricity shifting prospective was utilized within distributed multi-generation (DMG) system to formulate the upper limit of the potential reduction of the electricity flowing from the energy grid to this system without affecting a comfort level and an experience of energy users [191]. In study [192], a third-party energy consumption control for a defined group of users was considered for origination of the load-scheduling problem as a constrained multi-objective optimization problem. The optimization objectives were to minimize energy consumption cost and to maximize a certain utility, which can be conflicting and non-commensurable. A real-time pricing scheme reducing the peak-to-average load ratio in SG systems was utilized for the DR management in [193]. The proposed scheme addressed a two-stage optimization problem: maximization of payoff for energy users reacting to prices announced by the energy retailer; maximization of retailer's real-time prices in response to the forecasted users' reactions [193]. A distributed optimization algorithm established on dual decomposition without revealing users' privacy was developed in [66] to address spatial and temporal constrains of DR. A quick operation of this algorithm was obtained by implementation of binary search for this problem.

Residential DR is studied through scheduling of typical home appliances to minimize electricity cost and earn the relevant incentive. In one of the earliest approaches, a mixed integer nonlinear optimization model is built under a time-of-use electricity tariff [18]. After that, the modeling approach for peak shaving problem was presented through household loads scheduling using existing real-time scheduling algorithms [21]. In this approach, a set of the most common appliances is modeled considering their average power consumption during each operation cycle. Realistic assumptions are made on the daily usage of each appliance. A method of dynamic load priority (DLP) was proposed to manage the appliances on a house during a demand response event [177]. This method includes time and cost constraints ensuring the required comfort levels and uses context identification module, changing load's priority dynamically according to the technical characteristics of each load. A case study with two scenarios is presented considering a demand response within 30 min duration [21]. Residential energy management system combining DSM strategies with a minimization of consumer's cost and reduction of power consumption from the grid was developed [10]. This system considers the joint influence of energy price and carbon dioxide emissions as an environmental motivation to shift loads during peak hours. Rated power of appliances and demand response within 30 mins were utilized to formulate the optimization problem.

Majority of optimization methods for dynamic load scheduling are developed without considering any variations in load's power consumption during its operation. However, variation in appliance power consumption is an intrinsic characteristic of most household appliances such as washing machines, clothes dryers, dishwashers, etc. Using load profiles with high granularity (high sampling frequency), e.g., up to a fraction of a minute will lead to more accurate optimization analyses. Besides, an application of environmental factors hasn't been explicitly utilized as a generation constraint when local alternative energy sources are used. In addition to that, most of methods for dynamic load scheduling are developed based on complex mathematical models and require a large number of computational resources.

4.3.2 Developed model

The goal of current analysis is to show the opportunity to improve benefits of dynamic load scheduling when energy load profiles with high temporal sampling are utilized. To indicate such opportunity, household load scheduling is performed with various sampling frequencies of load profiles. In addition to that, a relative simplicity of mathematical model has been taken into account to reduce the requirements for computational resources. Due to this reason, a relatively simple "time-of-use" pricing scheme has been used for the conducted analysis [18].

Based on the developed optimization approaches (see section 3.3.1), current analysis can lead to achievement of various objectives, such as:

- minimizing the total energy cost;
- minimizing the operation delay to maintain a comfortable lifestyle;
- minimizing the cost of energy obtained from traditional energy sources;
- minimizing peak-to-average load ratio in smart grid system (e.g., peak shaving problem);
- maximize retailer's real-time prices in response to the forecasted users' reactions.

Pricing model is an important part of a load scheduling approach and dependent on the chosen optimization objective [12, 167, 186-188] . The main goal of pricing model in DDR is to dynamically match energy requirements of scheduled energy loads with the energy generation from available sources [19, 20, 175].

Scheduling decision is considered to be made at the operation level at the time when a certain appliance is turned on (either manually or automatically) and home energy management system (HEMS) communicates with this appliance to collect necessary information required for its scheduling such as its energy demand, earliest starting time, required comfort level and completion due date. Furthermore, HEMS retrieves the data about current pricing, which is usually updated a day in advance, and current energy availability from renewable and local energy sources. Given the described input data, HEMS needs to quickly find an optimized starting time for appliance's scheduling. A search of such starting time is performed under the following constraints: required comfort level, existing pricing scheme, current energy availability from renewable and local sources.

Several assumptions are made in the developed model. Following reference [189], only "flexible" appliances such as clothes washer and dryer, dishwasher, and electric oven have been considered for analysis of the developed model of dynamic scheduling. These appliances are further divided into delay-tolerant and delay-sensitive [189]. The operation of other appliances is assumed to follow the required comfort level, e.g., the operation of air conditioner should follow the required living conditions in household premises. Comfort level considerations have been obtained from the previous studies [172], [177]. The second assumption is about the arrival distribution for load scheduling requests. Following the presented assumptions on the daily usage of household appliances [21], the arrival distribution of loads scheduling requests is modeled for a regular weekday during a summer season. The data about energy load profiles with high sampling frequency have been obtained from experimental results [162]. The last assumption is that energy load profiles of all appliances are sampled with the same frequency. The corresponding adjustment of energy generation is assumed to be obtained from high ramp rate sources such as gas/diesel generators or other energy sources with a quick response, which will be available in the future. With these assumptions, the dynamic scheduling problem is to find an optimized starting time minimizing the required energy cost and satisfying the required comfort level.

The following notation is used to present a mathematical formulation of load scheduling problem:

Input Data:

$N =$ total number of appliances to be scheduled;

$a_i =$ arrival time of scheduling request for appliance $i \in N$;

$d_i =$ due date of scheduling request for appliance $i \in N$;

$oc_i =$ operation cycle of appliance $i \in N$;

w_i = delay-tolerance of appliance to be scheduled $i \in N$. $w_i = 1$ if appliance is delay-tolerant; 0 otherwise;

LP_i = load profile of appliance $i \in N$;

SF = sampling frequency of appliances' load profile defined by number of measurement readings in 1 min of appliance's operation cycle;

n = number of sampling time intervals in the operation cycle of appliance $i \in N$;

TW = scheduling time window represented by a vector of time intervals sampled with a required SF;

EP = energy pricing for scheduling time window sampled with a required SF.

Decision Variables:

x_i = start time of appliance $i \in N$;

y_i = completion time of appliance $i \in N$.

Then, for scheduling each appliance, the following optimization is formulated and solved.

Minimize requested energy cost $REC_i = EP(x_i, n) \cdot LP_i$

subject to $y_i = x_i + oc_i$ for $i \in N$

$x_i \geq a_i$ for $i \in N$

$y_i \leq d_i$ for $i \in N$

$x_i - a_i \leq comf_i$ for $i \in N$

$x_i \geq 0, y_i \geq 0.$ for $i \in N$

Dynamically calculated total energy profile (TLP) is the main result obtained during the performed scheduling. TLP shows energy distribution for the scheduled loads during the time elapsed from the beginning of scheduling until the current moment. The problem was coded in Matlab software based on the flow chart shown at FIGURE 22 below.

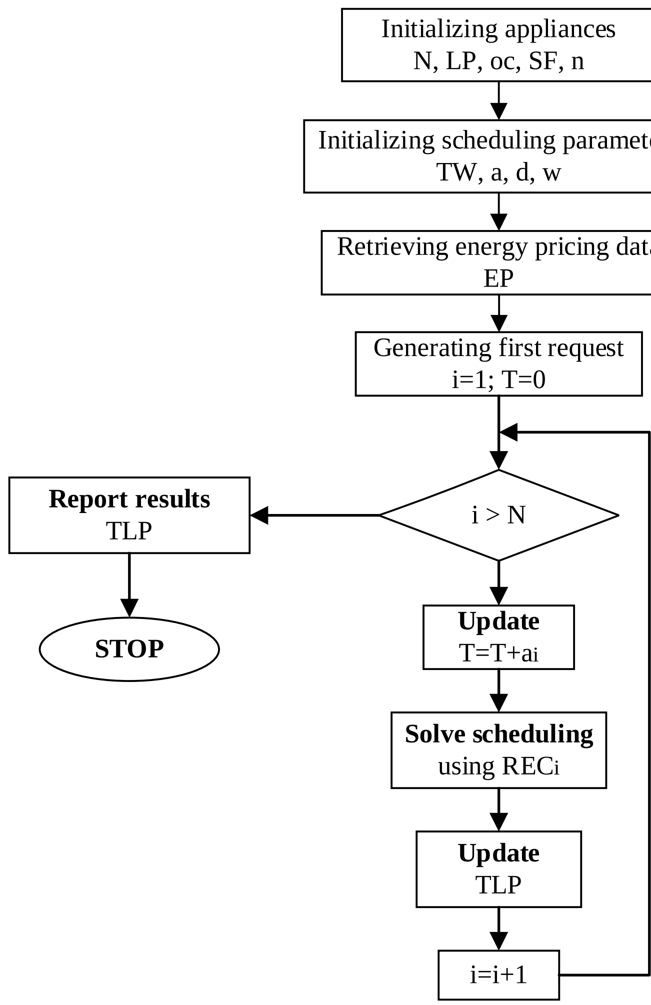

FIGURE 22: Flow chart of simulation implementation for dynamic load scheduling.

4.3.3 Simulation scenario

A typical residential user domain with 200 households has been considered for dynamic load scheduling implementation. The number and types of appliances in each household are obtained from the previous research study [162], which considered two types of residential households in Virginia state. Besides, energy load profiles (LPs) and their operation cycles for these appliances have been obtained from the same study. An illustrative example of energy LPs is provided at FIGURE 23 below. For simplicity, energy consumption of each appliance is shown based on its rated electric power. Since the obtained LPs were measured with 1 min and 1 sec time intervals [162], the corresponding calculation of REC has been performed. In addition to that, scheduling of appliances based on their rated power have been considered for comparison.

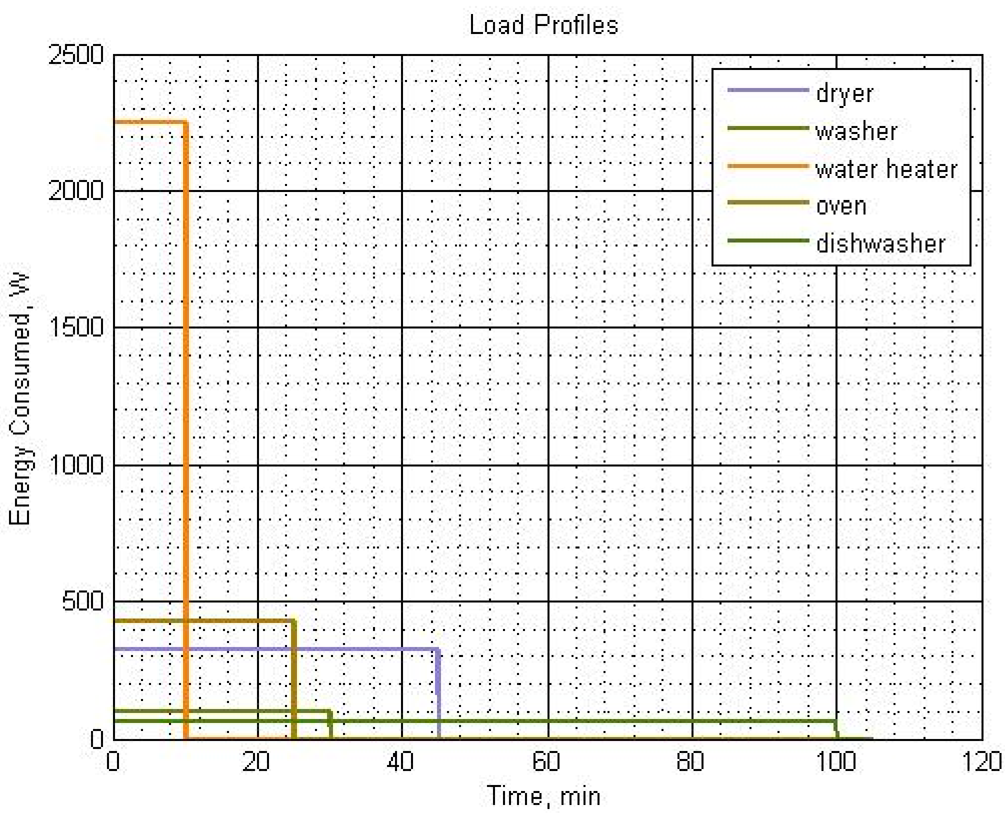

FIGURE 23: LPs for selected household appliances considered for dynamic scheduling.

A 24-hour scheduling time window (TW) is considered based on common availability of energy pricing information from the market [166].

4.3.4 Results and analysis

The TLPs for the developed scenarios with appliance LPs sampled with 1 min and 1 sec time intervals are shown in combination with scenario utilizing rated power of appliance LPs at FIGURE 24 and FIGURE 25 respectively. In spite of the fact that more experiments can be conducted to performed a detailed analysis, it can be observed that utilization of appliance LPs measured with a higher sampling frequency can increase the accuracy of TLP calculation with respect to utilization of rated power of appliances for dynamic load scheduling. Such increase in accuracy of TLP calculation in turn can improve the efficiency of dynamic load scheduling from various perspectives such as increasing load-shifting from peak to peak-off hour, decreasing peak-to-valley ratio, etc.

In the conducted experiment, it has been observed that peak-to-valley ratio of TLP has been decreased from 5.8 for scenario utilizing rated power of appliance LPs to 4.6 for scenario utilizing appliance LPs sampled with 1 min time intervals and to 4.3 for scenario utilizing appliance LPs sampled with 1 sec time intervals. In addition to that, the amount of energy shifted from peak hours to off-peak hours for scenario utilizing appliance LPs sampled with 1 sec time intervals is about 9% higher than for scenario utilizing appliance LPs sampled with 1 min time intervals.

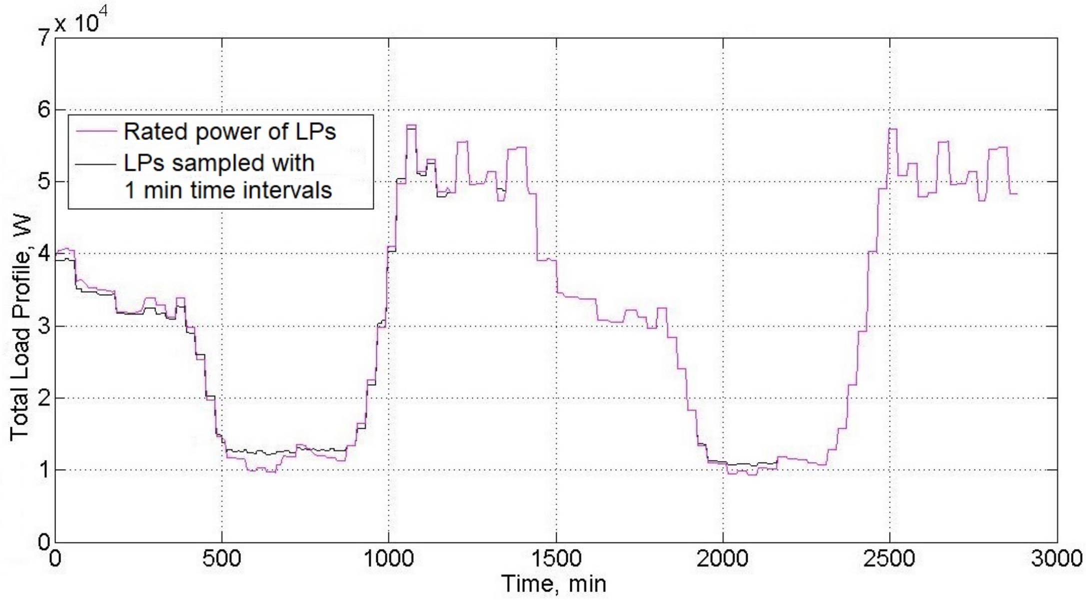

FIGURE 24: Total load profiles (TLPs) calculated for two scenarios: rated power of LPs and LPs sampled with 1 min time intervals.

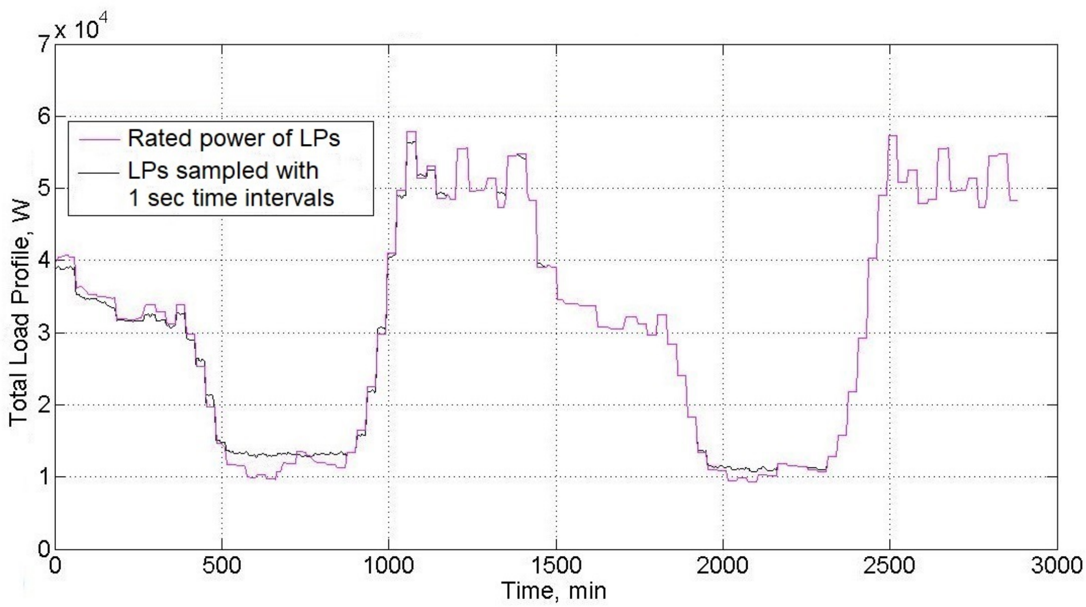

FIGURE 25: Total load profiles (TLPs) calculated for two scenarios: rated power of LPs and LPs sampled with 1 sec time intervals.

The developed simulation platform can be utilized for in-depth analysis of TLP's calculation for dynamic scheduling based on various scheduling algorithms, pricing schemes, distribution of arrival requests, and comfort preferences. This analysis can lead to enhancements in dynamic load scheduling optimization and development of more efficient energy pricing schemes. The main advantages of the developed simulation platform are following:

- scalability to various sizes of residential domains;
- flexibility of utilization various pricing schemes;
- relative simplicity.

4.4 Demand-based energy generation management

One of the latest achievements in the areas of distributed intelligence and M2M communication is a vast implementation of IoT sensors and emerging fusion in various domains of SG (see chapter 2). Such implementation leads to reduction of energy generated by traditional sources and allows high penetration renewable energy sources [194-197]. These facts in turn lead to cost-efficient energy distribution and anticipated reduction of carbon dioxide emission. However, an overall demand of electric energy is still constantly growing in all sectors of a typical SG (see FIGURE 26) [14, 50, 195, 198-200]. Hence, the need in developing advanced energy distribution algorithms and techniques is constantly increasing.

There are several applications for implementation of energy distribution algorithms and techniques within SGs. The major applications include energy consumption management for various users such as residential areas, commercial enterprises, and industrial sectors (see FIGURE 26), distributed multi-generation and its optimization, real-time electricity pricing control, and home energy management based on comfort control. While energy consumption management has been a focus of sections 3.2 and 3.3 of the current chapter, the current section focuses on distributed multi-generation of energy its control, and optimization.

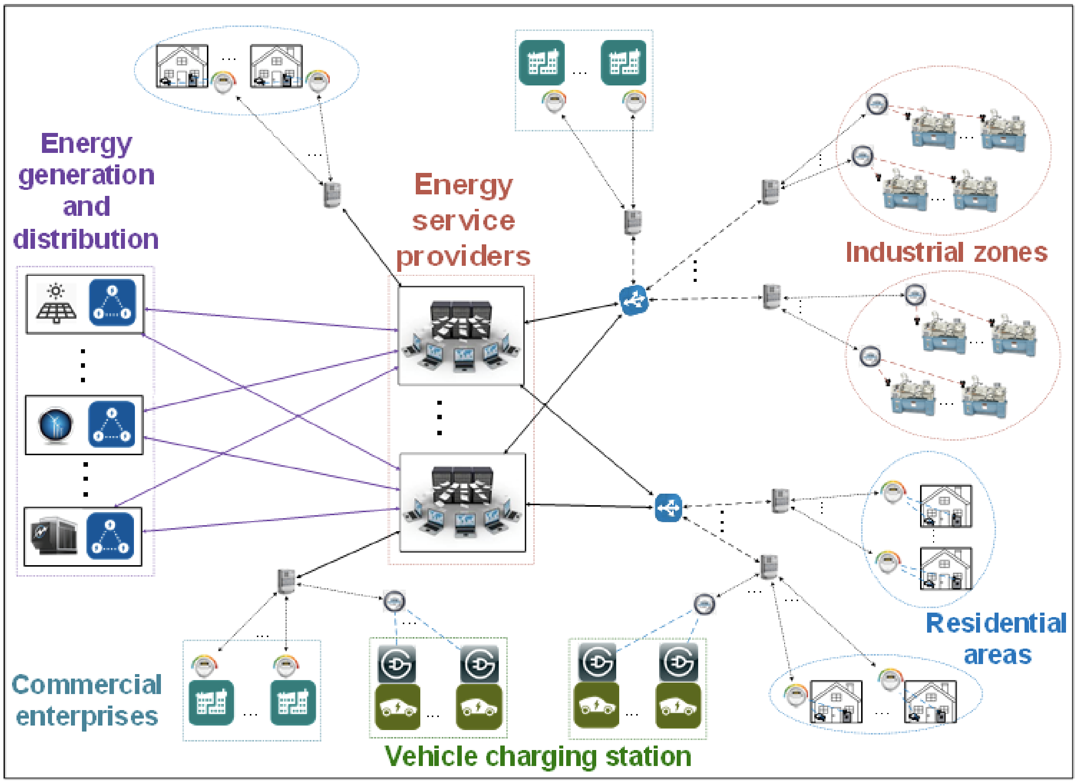

FIGURE 26: typical structure of energy distribution within smart grids.

To maintain an efficient energy distribution, one of the key concept of SGs' paradigm (see chapter 1), the operation of its energy sources have to be controlled [1-3]. Different control approaches such as classical control, robust control, wide-area control along with soft computing approaches like neural networks, fuzzy logic control, adaptive neuro-fuzzy inference system, genetic algorithm, particle swarm optimization and others were discussed in [201]. Besides, a comparative analysis of different methodologies is presented as a quick survey of the proposed solutions for enhancement of energy generation management [201].

Continuous growth of distributed energy generation led to creation of distributed power-generation systems (DPGSs). On one side, expanding deployments of DPGSs provides flexible energy utilization, which provides opportunities for dynamic energy consumption. On the other side, DPGSs present challenges due to a high penetration degree of renewable energy, among which wind and solar photovoltaics are typical sources [167, 201-205]. The integration level of the DPGS into SGs plays a critical role in developing sustainable and resilient power systems with highly intermittent renewable energy resources. Various approaches that were proposed to address these challenges have been summarizes in several studies [201, 203, 205]. It was shown that strategies for enhancing the connection and protection of the DPGSs belong to a special interest of ongoing research in distributed generation management filed [203].

Application of various optimization methods for distributed multi-generation is another important aspect of energy generation management. Extensive review of methods applied for energy generation optimization is presented in study [205] concluding that increasing penetration of DG levels require robust tools that help assess the capabilities and requirements of the networks to produce the best planning and control strategies. However, the study has indicated that, in spite of the fact that numerous strategies and methods that have been developed in recent years to address DG integration, widespread implementation of them has not taken place due to various implementation delays from network operator site.

A comprehensive framework was set up in Mancarella and Chicco (2013) [191] to analyze distributed multi-generation (DMG) systems for the purpose of identifying and quantifying their potential to participate in real-time DR methodology and programs. In this work, the novel concept of electricity shifting potential is deployed within the DMG system to establish the upper limit for the possible reduction of the electricity flowing from the electrical grid to this system without affecting customers comfort level and experience [191]. The modeling of an intelligent energy control center (ECC) for DGs using a multi-agent system has been presented in Manickavasagam (2015) [206]. In this work, a multi-agent system has been proposed to provide intelligent energy control and management in SGs based on the following benefits: extensibility, autonomy, and reduced maintenance. The DER model was created in a client and the ECC was created in the server. Communication between the server and clients is established using transmission control protocol/internet protocol (TCP/IP) [206]. The results show that the agent-controlling DER can be achieved from the server and clients.

Study [204] indicated that SGs had attracted significant attention as a high-quality and reliable source of electricity. Addressing energy generation management in SGs from economic efficiency and environmental restrictions points of view, two major direction of energy generation optimization were presented. The first direction is optimization of type and capacity of DG sources as well as storage devices. The second direction is development of operation strategy for energy generation in SGs. A master-slave objective function based on net present value (as an economic indicator) is proposed. Such objective function is solved using a hybrid optimization method including two steps [204]. In the first step, 2-D slave object functions (SOFs), operating costs, and consumer outage cost are minimized by quadratic programming and particle swarm optimization (PSO) algorithms with utilization of fuzzy logic. Using the best operation strategy from the first step, PSO algorithms employed to solve master objective function, and to determine the optimum capacity and type of DGs and SDs. The authors show that the proposed framework can be applied as an efficient tool in planning and energy generation management of SGs.

In a recent study [202], bundled generation and transmission expansion planning (BGTEP) was considered for solution of problems related to ascendant demand of power systems through optimal planning for a long-term period minimizing the cost of installation and operation. Due to the recent orientation toward renewable energy sources, the influence of wind farms is involved in the methodology. The uncertainty of wind power has been considered by a bounded and symmetric optimization approach combining two methods: robust and stochastic optimization [202]. A mixed-integer linear programming formulation of the BGTEP problem is obtained by alternative constraints in order to significantly reduce the level of complexity of the initially developed model [202].

Various machine learning approaches have been implemented to enhance the efficiency of energy distribution in SGs [207-212]. The approaches related to DR and energy generation management are of the interest of this chapter. One of the purposes of machine learning implementation in SGs is to create an effective algorithm selection between power system control algorithms depending on the state of a network. Such functionality can achieve better performance than the utilization of the same algorithm for every state [90, 213]. A novel method for creating algorithm selectors for power flow management on the IEEE 14- and 57-bus networks has been discussed in King et al. (2015). According to this method, the selectors were chosen from a diverse set of power flow management algorithms based on constraint satisfaction, optimal power flow, power flow sensitivity factors, and linear programming. The benefits of the developed method include minimization of overloads number and the curtailment applied to generators [213]. The other purpose of machine learning implementation in SGs is a real-time decision-making framework that can be effectively integrated with dynamic demand response schemes [37, 214, 215].

4.5 Summary

In this chapter dynamic energy distribution and management in smart grids have been covered from various angles: dynamic demand estimation and response, dynamic load scheduling, and demand-based energy generation. A capability of dynamic demand estimation has been presented as one of the applications of IoT sensors implementation in smart grids. Dynamic demand response is an important technique for dynamic energy distribution in smart grids. Increasing participation of residential energy users and charging of electric vehicles are the key aspects of the current state of dynamic demand response. Various load scheduling techniques based on corresponding optimization approaches were addressed in the previous studies to accommodate residential users in dynamic demand response scheme.

An opportunity to improve benefits of dynamic load scheduling has been introduced though developed mathematical model and performed simulation experiments. The introduced improvement opportunity is based on utilization of load profiles with high temporal sampling. The developed simulation platform allows to perform detailed analysis of the introduced improvement opportunity based on a chosen sampling frequency of load profile and utilized pricing scheme remaining scalable to various sizes of residential domains.

CHAPTER 5: ENERGY DISTRIBUTION FOR CHARGING OF AUTONOMOUS ELECTRIC VEHICLES

5.1 Charging of autonomous electric vehicles

Advancements in diverse technologies have propelled the growth, development, and deployment of unsupervised Autonomous Vehicles (AVs) [29, 216, 217]. High-capacity batteries with active energy management and quick charging capabilities are making the AVs suitable for everyday use. Intelligent, sophisticated sensor technologies such as 3D imaging, radars, LIDAR, ultrasonic sonars, laser scanners, and GPS are vital to the AV's situational awareness. Highly integrated processors and application specific electronics, very large-scale integrated circuits, navigation and guidance systems, robust and secure software are paving the way for the vehicle's full autonomy. In addition to that, AV capability enhancement is stimulated by artificial intelligence, big data analytics, IoT paradigm, robust networking platforms, and customized data centers [29, 216, 217].

It is expected that by 2030, sixteen million AVs will be roaming the roads in the US with the predicted growth of about 600,000 units per year [217-219]. Currently, the most popular Electric Vehicles (EVs) and their energy characteristics are shown in TABLE 10, where the charge time is calculated for 80% of the corresponding battery capacity. Based on the collected statistics related to the energy parameters of a wide range of currently distributed EVs [23, 28], battery capacity of 13.9 kWh with average charging rate of about 74 kW will require daily charging in 2030.

The average distances driven in the US metro areas by personal and service vehicles (with up to 6% of them estimated for personal use) are about 25 miles/day and 197 miles/day, respectively [220, 221]. Hence, the average vehicle charging frequency for the types listed in TABLE 10 are estimated in TABLE 11.

TABLE 10: Average power consumption parameters for most popular electric and plug-in hybrid electric vehicles in the US [222, 223]

Electric vehicle type	Battery size, kWh	Power acceptance rate, kW	Charge-Time, hours	Driving range, miles
Tesla Model S	81	19.2 - 120	3.4- 0.54	249 – 335
Tesla Model X				295
Chevy Volt	17.45	3.45	4	420 (53)
Ford Fusion Energi	7.6	3.3	1.8	550 (19)
Nissan Leaf	24	4.95	3.9	107

TABLE 11: Average weekly frequencies of visits to charging stations per vehicle – based on vehicle type

Vehicle	Average weekly frequency per vehicle		Refueling requirement
	Personal	Service	
Tesla Model S	0.6	4.72	No
Tesla Model X	0.59	4.67	
Chevy Volt	0.42	3.3	Yes
Ford Fusion Energi	0.32	2.5	Yes
Nissan Leaf	1.64	12.9	No

Thus, the total numbers of personal and service EVs that will require charging each day in the US will be about 1.4 million and 700,000 in 2030. That will require about 18.5 GWh of energy to be generated daily in the US alone [29]. Additionally, the expected charging time will be reduced significantly [29]. Beside electrical based AVs, we expect gasoline and Liquefied Petroleum Gas (LPG) to continue fueling the AVs [224]. Unsupervised AVs will create paradigm shift, new economies, require businesses to upgrade their existing servicing platforms, and build new infrastructure based on the region and service needs. Since the majority of AVs are battery-based, the current analysis is targeted to them and can be further extended to the market of other vehicles.

Infrastructure of autonomous charging station is an innovative application of energy distribution in SGs. An automated secure, resilient and safety critical hybrid charging station architecture for unsupervised AVs is proposed in the next section. Besides, servicing flow, analytical framework, and online scheduling procedure are presented for the proposed architecture. Potential locations for such charging station include private residences, selected areas within parking lots of high-rise offices or residential buildings, mall and commuter parking lots, and other dedicated areas.

5.2 Autonomous charging/refueling station

5.2.1 Servicing flow and layered architecture

In a completely autonomous charging station architecture, as illustrated FIGURE 27, we envision various types of unsupervised AVs to arrive at the station with respective arrival rates. Upon entering the periphery of a charging station, they will go through the following stages: classification, queue assignment, servicing at the charging pump, and payment followed by exit.

Arriving AVs will go through a classification booth (or an automated classification process), where the charging station and AVs will exchange credentials and parameters, such as battery capacity required for charging; wired or wireless charging, available power acceptance rates; fuel types: gasoline, diesel or LPG; and charging/fueling priority. This exchange will lead to Quality of Service (QoS) determination and a queue assignment. For example, emergency AVs will be directed to the highest priority queue with the least service waiting time. Other queues can be related to two service categories. The first group is a diverse duration: medium, fast, and ultra-fast electric charging (see FIGURE 27). The second group is various fuel type: gasoline, diesel or LPG. Typical electric charging times are summarized in Table 12 [225, 226].

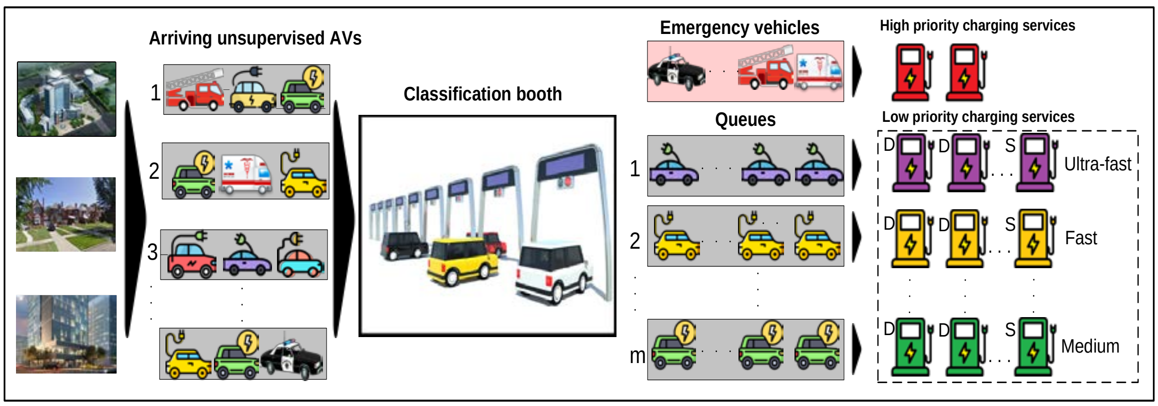

FIGURE 27: Traffic flow within an autonomous charging station. Designated (D) and sharable (S) pumps are considered [29].

The charging stage will start from a dynamic alignment and physical docking of AVs with the charging/fuel pump's interconnects/nozzle. After docking, the AV and the charging station will exchange credentials: dual authentication, amount of charge/fuel required, and financial information. After that, charging (or fueling) of AVs to predetermined limits will be performed and continuously monitored. At the final phase of the charging stage, receipts for the rendered services will be generated and exit path will be assigned.

TABLE 12: Charging speeds of commercially available charging stations [225, 226]

Speed	Value, kW	Time to full charge, hours	Application
Slow	> 3	6-8	Overnight at home
Medium	7-22	3-4	Commercial and public on-street
Fast	>43 (AC) >50 (DC)	0.5	Same for compatible EVs
Ultra-fast	50-400	>0.25	Same for compatible EVs

In developing the architectural and analytical framework, layered approach has been proposed (see FIGURE 28), and briefly describe the function and role of each layer.

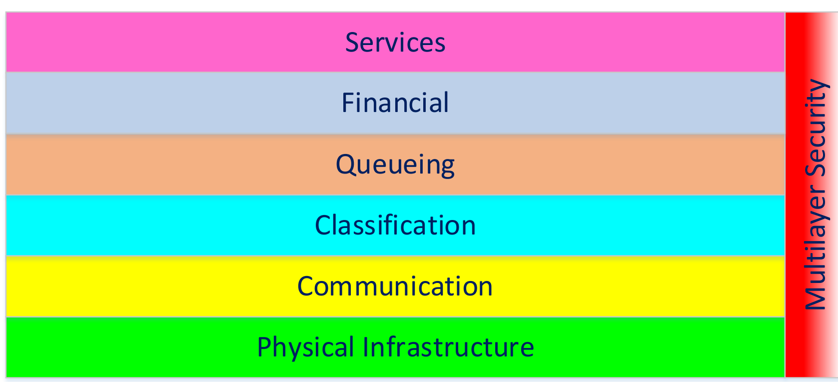

FIGURE 28: Traffic flow within an autonomous charging station. Designated (D) and sharable (S) pumps are considered.

The Physical Layer consists of the power generators (that could use renewable energy sources, natural gas or diesel fuel for generation and optional connection to a major grid) along with their control and monitoring gear; electric chargers or fuel pumps; security cameras; wireless and/or wired networking equipment; computer servers; and associated hardware. The power generation can be based on micro-grid architecture which can be either grid connected or islanded mode. In addition to the power generators, automated charging/refueling pumps will be the key technological components of charging/refueling service. Early implementations are robotic based, and rely on the fusion of vision guidance and supporting sensor data (e.g., optical pattern recognition, 3D proximity sensor, etc.) to align and insert the external charger into the car's charging receptacle. A typical robotic apparatus is a 6-axis articulated "robot arm", used in a vast variety of industrial applications (e.g., automated production lines, welding, material handling, assembly and test, laser drilling, semiconductor fabrication, etc.), where seamless integration of vision guidance and robotic motion has been demonstrated. The snake-arm type robot is an interesting alternative to the more traditional robot arm, comprised of multiple links separated by 2 degrees of freedom joints, resulting in a very high amount of cumulative bend [227]. Vision systems typically include structured light for illumination consistency, optical sensor arrays for image capture, digital signal processing, and interpretive algorithms. Depth mapping augmentation is made possible with techniques, such as imaging LIDAR (Light Imaging, Detection and Ranging) or innovative depth sensing enhancement leveraging with polarization cues [228]. The technology for precision visual-guidance applied to robotic manipulation has been available for some time now. The primary development areas, with respect to supporting the charging stations' feasibility, are likely to be targeted around cost reduction.

The Communication Layer handles the information exchange between the AVs and the charging station processing servers, utilizing cellular or wireless networks. The Classification Layer matches the needs of the AVs with the capabilities of the charging station and then directs the AVs to the appropriate queues. The Queueing Layer will be based on a flexible queueing system, in which incoming users (AVs), prioritized by their service requirements (e.g., fuel type and service duration constraints), are paired with the most suitable servers (i.e., charging pumps) pre-categorized by charging capability and capacity. The Financial Layer will support vehicles' authorization and payment transactions for the rendered services. The Services Layer will charge/fuel AVs based on information exchanged between the lower layers. A multilayer security model has to be adopted to ensure protection ranging from physical infrastructure (e.g., AVs and charging stations) to the information exchange and financial transactions.

Classification and queueing layers of the described framework are the main focuses of current research. The operation of both of these layers is based on the information exchange between vehicles and the charging station. It is considered that charging stations will provide current pricing information updated in real-time on web (e.g., using online advertisement platform [229]). At the beginning of the information exchange, vehicles connect to a charging station based on its location and announced pricing. The choice of a particular charging station is based on user-defined requirements for traveling distance and acceptable level of pricing. This problem has been solved previously and, hence, have not been addressed the current research. After the initial connection to a charging station, each vehicle sends it a reservation request message with their energy consumption parameters, such as required amount of energy, its acceptance rate (or tier of charging), and timing requirements, such as earliest arrival time and charging deadline. When the charging station receives this message, its classification layer defines all pumps for charging of a particular vehicle and their sequence based on pre-defined priorities. For this sequence of charging pump, queueing layer processes the corresponding reservation request based on its timing and energy availability constraints. Specifically, queueing layer follows the provided sequence of pumps and schedules a particular vehicle in pump's queue that satisfies timing and energy requirements. Overall, queueing layer presents a complex model consisting of multi-class AVs with various power acceptance availability and multi-class servers with different capability.

In the next subsections, analytical framework describing queueing and classification layers is presented. This framework is followed by online scheduling problem with an illustrative example.

5.2.2 Analytical framework

In order to establish a robust architecture, we propose development of an analytical framework based on the previously described set of statistical data related to energy parameters of Autonomous Electric Vehicles (AEVs) and charging stations. The analytical framework enables the management of optimal power generation based on the dynamic demand for recharging/refueling services [230-232]. Moreover, the analytical framework leverages the unsupervised AV's flexibility, stemming from their ability to travel to a charging/refueling station when they are not in use (especially during late night/early morning hours). This autonomous charging scenario will help convert the nonhomogeneous arrival rates of conventional non-AVs (e.g., rush hour traffic) to more homogeneous arrival rates over the period of twenty-four hours. We expect the charging station arrival rate to undergo a distinct change, transitioning from user-operated vehicles to the unsupervised AVs [233, 234]. The charging stations will provide current pricing and waiting times updated in real-time. The AVs will monitor this information and schedule their charging station visits accordingly. Such targeted information exchange can be based on advertisement platform discussed in the reference [229]. A tightly coupled supply and demand analytical framework can lead to the optimal use of resources at the best prices [230-232].

The arrival rate of different types of AVs in a US metro area will depend on the following statistical parameters: estimated population of AVs, the average driving range on the full charge/full tank, and the average distance traveled daily in a typical US metro area (see TABLE 10). The charging/refueling station's queueing system presents a complex model consisting of multi-class AVs with various power acceptance availability and multi-class servers with different capability. One promising approach to managing queueing complexity is through the *pooling* of various types of AVs and charging pumps [235].

As an illustration of system flexibility, consider the Tesla Model X and S, which can be serviced with any of the charging speeds listed in TABLE 12. In comparison, the other types of vehicles listed in TABLE 10 have a limited charging flexibility and cannot benefit from ultra-fast or fast charging pumps. Aggregation of various vehicle types and charging services makes this queueing model more complex than traditional ones [230, 236].

As a common approach for modeling of steady homogeneous arrival process [14, 22], a Poisson Process has been considered to describe the arrival behavior of AVs [29]. Although this process can be derived for most of random arrivals [230, 237], other random arrival distributions can be utilized to demonstrate system's performance under the special conditions, e.g., traffic congestion. Independent increments in this process occur with a probability of a single arrival during a short time period h being $\lambda_a h$ [238, 239]. In this case, λ_a denotes the hourly arrival rate of AV type a. Let N_a and f_a denote the number of AVs of type a in the region and the average weekly frequency of visits per week (see TABLE 11), respectively. Hence, the hourly arrival rate can be estimated by $\lambda_a = \frac{f_a N_a}{24\times7}$. Furthermore, $r \in [0.1,0.9]$ denotes the state of charge (SOC) showing, in the example of EVs, the ratio of required energy for charging to the whole battery capacity for each vehicle in a given region.

Upon arrival, all vehicles are classified and directed to the appropriate queues (see subsection 1.2.1). Charging pumps can also be pooled into equally capable multiple servers to address charging capabilities varying by their rates for different types of these services. In consequence, a multi-server queueing model, M/M/c or M/G/c, is proposed [238, 239] for this framework. In this pooled queueing system, the queue discipline can be simplified to “first come first serve” with a priority line override for emergency vehicles.

As far as the performance criteria of the queueing system are concerned, the key performance measurements of a queueing model are the average time in queue and the time average number of AVs in this queue. Once pooled, performance of this queueing model can be analyzed in its steady-state [236, 240] from either M/M/c or M/G/c model.

A discrete-event simulation is an alternative to an analytical approach [236]. Unlike an analytical approach, a discrete-event simulation does not give the exact solution for the developed queueing model. However, it is scalable for systems with high complexity. Due to this fact, a discrete-event simulation can be considered as a viable solution for the developed queueing model. Besides, a discrete-event simulation can also be used to verify the analytical approach.

Energy consumption requirement is an important source of charging station's operation. Hence, estimation of its power consumption at any instance of operation is a key feature of this framework. Processing charging reservation requests at queueing and classification layers, automated charging station continuously estimated its energy consumption, which will be provided as a feedback to energy generation domain of a smart grid. Since this feedback will be provided in a real-time, the described operation of automated charging station can be considered as an application of dynamic energy distribution in smart grids.

The pricing model is another important part of the analytical framework [237], dependent on the optimal classification and assignment of AVs to the queue (optimally matched to AV service requirements: minimum service time and best price). Each queue can have different service features, driving the associated price in units of $/kWh. These prices will change dynamically based on a relationship between AVs' arrival rate, corresponding energy demand, and the charging/refueling service offered by the stations. The goal of the pricing model is to dynamically match energy requirements of arriving AVs with the energy generation and storage from available sources [230, 231, 237].

The envisaged analytical framework can be optimized to achieve certain objectives, such as:

- minimizing mean waiting time;
- minimizing mean total time in the facility;
- minimizing mean number of vehicles in the facility;
- minimizing number of vehicles rejected due to full occupancy;
- minimizing daily operation cost;

- maximizing daily profit.

Various techniques such as simulation optimization, mixed integer programming, and stochastic optimization can be investigated depending on the scope of the problems. As the first step of the series of investigations, an online scheduling problem is proposed in the next subsection.

For a given traffic pattern and chosen design of charging station, the performance measurements to assess its operation will be provided by the analytical framework. These measurements include the number of vehicles rejected from charging service in each tier and tier utilization of charging pumps. In addition, a scheduling and rejection calendar and energy consumption profiles are obtained to demonstrate the results of charging station's operation.

5.2.3 Online scheduling

In the charging station system, there are different levels and time epochs where decisions need to be made. In the developed architecture of autonomous charging station, the three main levels of decision-making (from top to bottom) include a choice of the total number of pumps in each tier; a choice of the number of sharable pumps in each tier; and an operational level scheduling when a new vehicle arrives to the system (see FIGURE 29). Such scheduling considered to be performed online is the main focus of the current research.

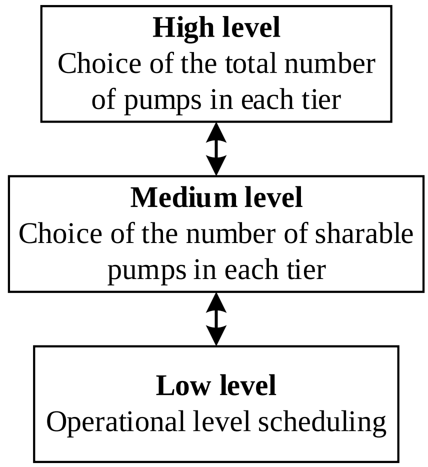

FIGURE 29: Main levels of decision-making hierarchy in an autonomous charging station.

Online scheduling decision is made at the operational level at the time when a new vehicle initiates a transaction with the charging station system. Upon the initiation of the transaction, the transaction system communicates with the new vehicle to collect necessary information pieces such as its charge acceptance rate, energy demand, earliest arrival time, and charging due date. Furthermore, the system also retrieves the data that describe the current status of the charging station, including the arrival times, charging times, and due dates of the existing vehicles in the system. Given this input data, the transaction system needs to quickly find a charging plan for the new vehicle if it is feasible, or to quickly reject the request of the new vehicle if there is no feasible slot for charging it. Note that this decision must be made online within seconds (i.e., in real-time). We propose a 'divide-and-conquer strategy' for this online scheduling as described below.

In order to design the online scheduling procedure, several assumptions are made. It is assumed that an "opportunistic charging" can occur: whenever there exists an idle pump and if a vehicle is in the on-site queue (i.e., waiting in the designated parking area without being served), the vehicle is charged by the currently idle pump. If there are more than one vehicles are waiting, apply the EDD (earliest due date) first rule, i.e., the vehicle that has the earliest due date is given the highest priority. When the next scheduled vehicle arrives at the pump, this unscheduled charging service must be stopped and the vehicle returns to the on-site queue (with updated energy demand as it has received the opportunistic charging service). The second assumption is about sharing pumps with vehicles having acceptance rates in a different tier. Suppose that vehicles and pumps are multiple tiers depending on charging rates. It is optimal to charge a vehicle at the pump in the same tier. Due to the nature of uncertainty, demand and supply in each tier can be unbalanced and it becomes unavoidable to use some pumps in one tier to charge a vehicle in another tier with a downgraded charging rate. Hence, there are some number of pumps in each tier that are designated to be shared by vehicles in other tiers. The last assumption is that when a new vehicle is scheduled, the relative positions among vehicles that are already queued in each pump are not disrupted. With these assumptions, the online scheduling problem is to find a feasible place in a specific queue for the new vehicle. The criterion used in this problem is to minimize the sum of charging completion times of all vehicles in the queue including the new vehicle.

To be more specific, consider an online scheduling problem for a pump $k \in K$, where K is the set of pumps in the charging station. The following notations have been used to present a mathematical formulation for the online scheduling problem:

Input Data:

$N_k = \{1,2,\dots,n_k\} =$ index set of existing vehicles assigned to pump k at the time of scheduling a new vehicle N. N_k is a totally ordered set, where $i < j$ for $i,j \in N_k$ implies that vehicle i is charged before vehicle j.

$a_i =$ arrival time of vehicle $i \in N_k$ $(= 0$ if arrived already)

d_i = due date of vehicle $i \in N_k$

c_i = charging time of vehicle $i \in N_k$ at the current queue

w_i = penalty imposed on the completion time of vehicle $i \in N_k$

a_N = earliest arrival time of new vehicle

d_N = due date of new vehicle

c_N = charging time of new vehicle at the current pump

w_N = penalty imposed on the completion time of new vehicle

$y_0 = 0$ defined for the sake of simplicity of formulation

Decision Variables:

x_i = start time of charging vehicle $i \in N_k$

x_N = start time of charging new vehicle

y_i = completion time of charging vehicle $i \in N_k$

y_N = completion time of charging new vehicle

$z_i = 1$ if new vehicle is placed right before vehicle i for $i \in N_k$; 0 otherwise

$z_L = 1$ if new vehicle is placed after vehicle n_k; 0 otherwise

Then, during the transaction with a new vehicle, the following optimization is formulated and solved for the pump k.

Minimize $\sum_{i=1}^{n_k} w_i y_i + w_N y_N$

subject to $y_i = x_i + c_i$ for $i \in N_k$

$y_N = x_N + c_N$

$x_i \geq a_i$ for $i \in N_k$

$x_N \geq a_N$

$y_i \leq d_i$ for $i \in N_k$

$y_N \leq d_N$

$x_i \geq y_{i-1}(1 - z_i) + y_N z_i$ for $i \in N_k$

$x_N \geq y_{i-1} z_i$ for $i \in N_k$

$x_N \geq y_{n_k} z_{last}$

$\sum_{i \in N_k} z_i + z_{last} = 1$

$x_i \geq 0, x_N \geq, y_i \geq 0, y_N \geq 0;\ z_i, z_N \in \{0, 1\}$.

The objective function represents the sum of weighted completion times. If there is no priority is given, $w_i = 1$ for all i can be used. First two constraints state that the charging completion time is the charging start time plus charging time. Next two constraints enforce that charging can start only after the vehicle arrives at the station. Following two constraints ensure that completion of charging must be within the due date. Next three constraints make sure that the charging a vehicle (say vehicle A) can start only after completion of charging the vehicle (say vehicle B) in front of A, where B can be either the new vehicle or the same vehicle that was scheduled before A prior to the arrival of the new vehicle. The last constraint will ensure that only one place in the queue is chosen for the new vehicle.

In an alternative approach, the objective function of the makespan can be applied. Therefore, the criterion used for this approach is to minimize the time that elapses from the beginning of charging of all vehicles in the queue including the new vehicle to the end. In this case, the described optimization formulation will be updated by the following variables and conditions:

Additional Decision Variables:

$\boldsymbol{V_k}$ = makespan of pump k

Minimize the objective function V_k

subject to $V_k \geq y_i$ for $i \in N_k$

$V_k \geq y_N$,

$V_k \geq 0$

The added constraint confirms that the makespan is an upperbound on completion times.

Note that this problem is a mixed-integer nonlinear programming. The bilinear terms are products of one binary and one continuous variables, and it is straightforward to linearize those terms by adding lower and upper bounding constraints. As a result, the formulation becomes a mixed-integer linear program, which can be solved via any off-the-shelf solver.

The developed model considers optimal scheduling procedure that occurs every time when a specific pump is under consideration. Pump assignment is performed based on the following criteria: high priority pumps are allocated for the same tier vehicles; low priority pumps are utilized for servicing cars from different tier based on their real-time availability at the moment of new car arrival. Besides, if multiple pumps satisfy both, due date and assignment criteria, the smallest total completion time of vehicles currently in the queue is preferred as a tie-breaker in selecting the pump. If all pumps of a charging station are occupied and not available for scheduling of the new vehicle, the charging request will be rejected. In that case, the vehicle can be referred to another station within a smart grid. Such “reject & referral” concept can increase the efficiency of utilization of smart grid’s resources and sustainability in congestion situations, whose occurrence will be initially minimized by an optimal choice of charging pump’s rate in each tier and type (designated and sharable).

5.2.4 Illustrative example of online scheduling

An illustrative example of this optimal real-time scheduling procedure considers 10 charging pumps and 30 vehicles that were scheduled for charging at these pumps as illustrated at FIGURE 30. The corresponding parameters of these vehicles are provided in TABLE 13. It is assumed that the arrival of vehicles follows a Poisson distribution with a rate of 6 arrivals per hour. Energy demand required for charging of each type of vehicle is assumed to be 70-90% of the corresponding vehicle’s battery capacity, which is considered as an average battery capacity for the most popular vehicles of this type. Charging times are calculated based on the energy demand of the vehicle, the acceptance rate of the vehicle, and the charging rate of the assigned pump. Charging due dates are assumed to be 120 min, 300 min, and 480 min from the corresponding arrival time for vehicles of tier 1, 2, and 3, respectively. The penalty parameters, w_i, are set to ones in this illustrative example, but it is not difficult to accommodate different penalty values, which can be possibly introduced for special types of vehicles having higher priorities (e.g., emergency vehicles).

In this example, all pumps of the charging station are divided into 1st, 2nd, and 3rd tiers. The number of pumps in each tier was chosen based on the statistical distribution of vehicles belonging to different types of energy acceptance rate. As mentioned earlier, the concept of sharable pumps has been introduced in this scenario. According to this concept, each tier will have two types of pumps: designated and sharable. Designated pumps can only be utilized for charging the vehicles of the same tier only. Whereas, sharable pumps can be used for charging vehicles from a different tier based on their real-time availability. Following this concept, pumps 2, 5, 9, and 10 are considered to be sharable at tiers 1, 2, and 3 as shown at FIGURE 30.

TABLE 13: Parameters of vehicles considered in scheduling procedure

Vehicle ID	Vehicle Type	Energy acceptance rate, kW	Battery capacity, kWh	Energy demand, kWh	Charging time, mins	Arrival time, mins	Due date, mins
1	3	120	81	67.46	33.73	0	120
2	2	6.6	20	16.59	150.78	0	300
3	2	6.6	20	17.16	156.04	0	300
…	…	…	…	…	…	…	…
28	2	6.6	20	15.75	143.22	219	519
29	1	3.3	14	10.62	193.07	229	709
30	1	3.3	14	11.23	204.23	238	718
31	2	6.6	20	15.97	145.14	246	546

In the presented snapshot, the new 31st vehicle belonging to the second tier is considered for scheduling during the transaction when the time is reset to zero (see FIGURE 30). Pump 3 is first assigned and the scheduling problem is solved. The solution places the 31st vehicle in front of the 28th vehicle at pump 3. The problem was coded in

Matlab™ software and Gurobi™ optimization solver was called to solve the mixed-integer linear program in the previous section.

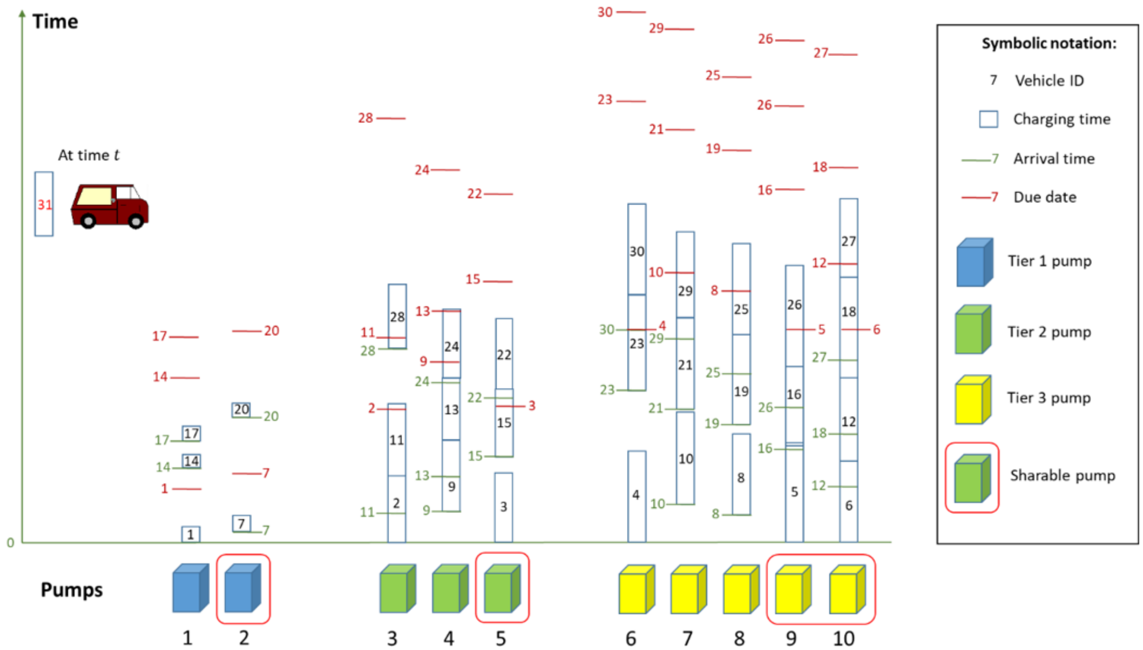

FIGURE 30: An example of optimal scheduling procedure scenario represented as a snapshot at the time of new vehicle arrival. Sharable pumps in each tier are framed in red.

5.3 Simulation implementation of online scheduling

5.3.1 Analytical platform

Following the proposed mathematical formulation of an online scheduling procedure, its implementation through a discrete-event simulation has been performed. Specifically, this procedure has been repeatedly applied for scheduling of each vehicle connected to the charging station within the specified time frame. The flow chart describing the simulated implementation of an online scheduling procedure is provided at FIGURE 31. Overall, this implementation consists of three main phases or modules: vehicle data generation; pump data generation; queueing and scheduling. *Vehicle data generation* phase contains vehicle initialization, generation of exponential random variable, and generation of scheduling parameters steps (FIGURE 31). *Pump data generation* phase includes initialization of pumps, definition of pump selection rule, and read vehicle data steps (FIGURE 31). *Queueing and scheduling* phase includes initialization and corresponding update of the current clock time and information about serviced vehicles and operating pumps. Besides, this phase includes pump's selection for each scheduling problem and solution of this problem for each vehicle initialized at vehicle data generation phase. In addition to that, the final results of scheduling are reported at the end of optimal scheduling phase (FIGURE 31). A detailed description of main steps belonging to each phase in the flow chart is provided below.

Steps of vehicle data generation phase:

- "Vehicle initialization" block defines the initial parameters of arriving vehicles:
    - Vehicles' arrival rate: λ;
    - Vehicles' distribution in each tier: $R_1, R_2, \dots, R_N$;
    - Vehicles' distribution in walk-in or reservation requests' types: R_W, R_R;
    - Maximum number of vehicles simulated: Veh_{max}.
- "Generate an exponential random variable" block generates a continuous random variable that represents an inter-arrival (IA) time and follows an exponential distribution based on the defined arrival rate: IA~Exp(1/ λ). In this case, the number of vehicles arrived in a certain time interval will be defined by a discrete Poisson distribution. Exponential distribution was chosen because it can be derived for most of known arrival processes with the minimum number of assumptions. For a critical system condition describing an unexpected vehicle arrival rate, any random arrival distribution can be considered in the model.

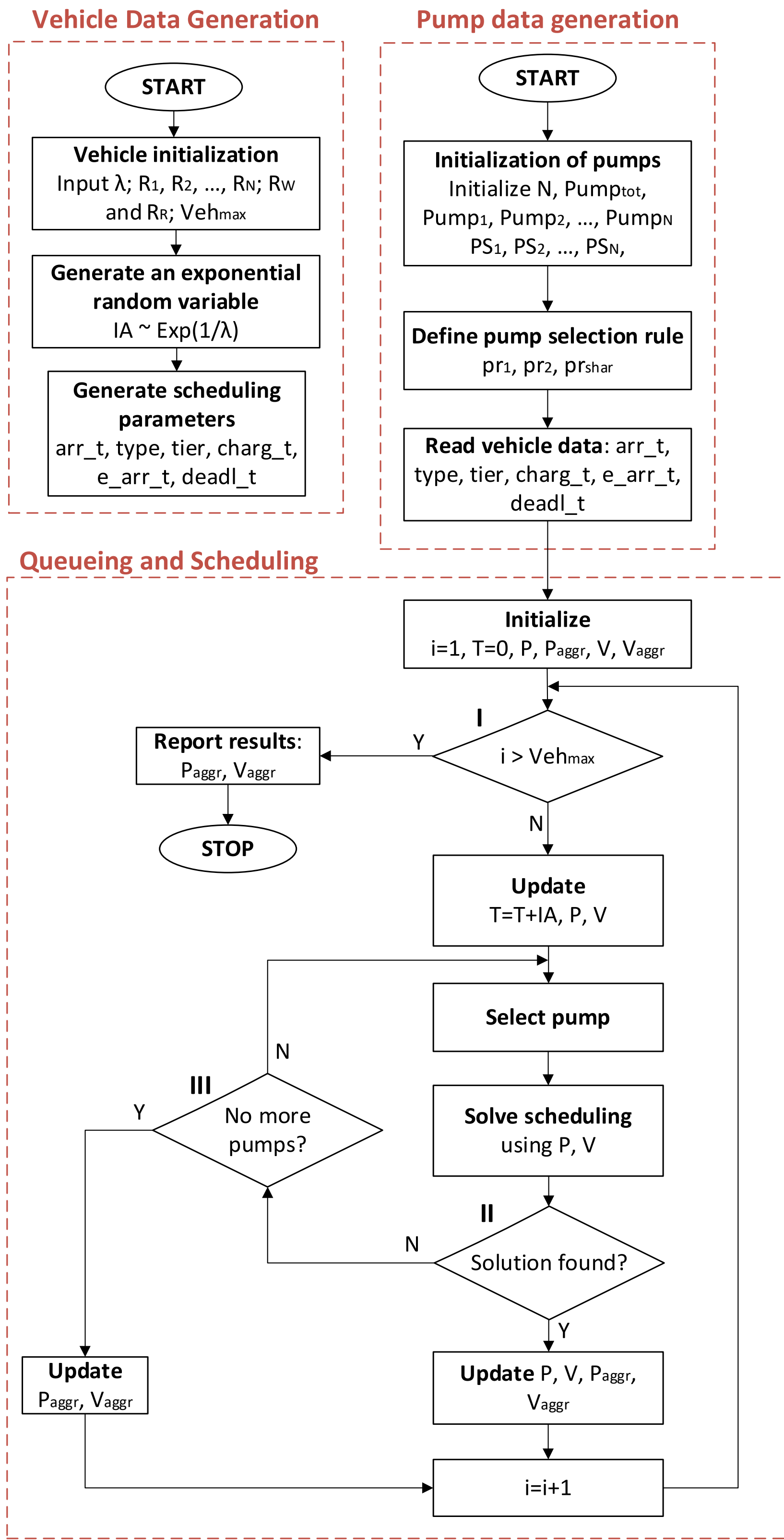

FIGURE 31: Flow chart of a simulation implementation of the online scheduling procedure

- “Generate scheduling parameters” block defines vehicles’ information that will be directly used for solving of their scheduling problems:
    - arr_t – time when each scheduling request arrives to the system. It follows exponential distribution with inter-arrival rate generated by continuous random variable;
    - type of each scheduling request: reservation or walk-in;
    - tier of each vehicle;
    - charg_t – required charging time defined from the energy parameters of each vehicle;
    - e_arr_t – earliest arrival time required for each vehicle to reach the charging station;
    - deadl_t – due date for charging each vehicle.

Steps of pump data generation phase:

- “Initialization of pumps” block defines the initial (higher-level decision) parameters of a charging station:
    - The number of tiers: N;
    - The total number of pumps: $\mathrm{Pump}_{\mathrm{tot}}$;
    - The total numbers of pumps in each tier: $\mathrm{Pump}_1, \mathrm{Pump}_2, \dots, \mathrm{Pump}_\mathrm{N}$;
    - Numbers of sharable pumps in each tier: $\mathrm{PS}_1, \mathrm{PS}_2, \dots, \mathrm{PS}_\mathrm{N}$;
- “Define pump selection rule” block determines the sequence of pumps that will be further used for solving of scheduling problem at a certain tier. This sequence of pumps is based on three priorities: pr_1 is used for designated pumps of the same

tier, : pr_2 is used for sharable pumps of the same tier, and $\mathrm{pr}_{\mathrm{shar}}$ is used for sharable pumps of higher tier.

- "Read vehicle data" block retrieves the scheduling parameters obtained in vehicle data generation phase.

Steps of queueing and scheduling phase:

- "Initialize" block defines the following parameters of the system:
  - vehicle i that is being currently served;
  - $\mathrm{T} = 0$ – simulation starting time. After that, T is considered as a current clock time.
  - P – current state pumps matrix showing pumps' tiers, e.g., ultra-fast, fast, and medium, pumps' types: sharable or designated, and vehicles currently scheduled for these pump (i.e., currently in the system);
  - $\mathrm{P}_{\mathrm{aggr}}$ – overall pumps matrix showing parameters their tier and type (in a manner similar to matrix P), and all vehicles that have been served and currently in the system;
  - V – current state matrix showing vehicles' scheduling parameters along with their scheduling results for vehicles that are currently in the system;
  - $\mathrm{V}_{\mathrm{aggr}}$ – overall matrix showing vehicles' scheduling parameters along with their scheduling results for all vehicles that have been served and currently in the system;

- Condition I checks if all vehicles have been simulated. If the condition is "Yes", then the results are reported in terms of P_{aggr} and P_{aggr} matrices and scheduling is being finished. Otherwise, Condition I forwards to "Update" block.
- "Update" block updates P to the current clock time and sequentially modifies P and V matrices based on this clock time by removing vehicles that have been serviced already at the current time T.
- "Select pump" block chooses the pump from the sequence determined by "Define pump selection rule" block for a given tier.
- "Solve scheduling" block formulates a mixed-integer linear programming problem for scheduling a vehicle at the chosen pump's queue and uses optimization solver to compute a possible scheduling solution (if any) for this problem based on information in matrices P and V.
- Condition II checks if the feasible solution is found. If the condition is "Yes", then vehicle is queued at the chosen pump, matrices P, V, P_{aggr}, and V_{aggr} are updated, and vehicle $i + 1$ is considered for scheduling starting from Condition I. Otherwise, it follows to Condition III.
- Condition III checks if there are no pumps left in the sequence determined by "Define pump selection rule" block for a given tier beside the previously chosen ones. If the condition is "Yes", then scheduling cannot be completed at the current charging station and matrices Paggr and Vaggr are updated with a rejection result for the current vehicle. Otherwise, it follows to "Select pump" block.

The described implementation is based on several assumptions and concepts. In the vehicle data generation phase, the maximum number of vehicles simulated (Veh_{max})

should be large enough for the system to be considered in a steady state. Additionally, the energy required for charging of each vehicle is assumed to be randomly distributed between 70% and 90% of its battery capacity. Hence, charging time (charg_t) for each vehicle is defined as a ratio of the energy required for charging this vehicle to the corresponding energy acceptance rate of vehicle's tier. Besides, it is assumed that the earliest arrival time (e_arr_t) is defined based on the average range of distances between residential/commercial premises and the charging stations. Charging due date (deadl_t) is randomly distributed and the lower vehicle's tier the larger is the charging due date for it.

In the pump data generation phase, it is assumed that the number of tiers for charging pumps (N) is the same as it is for arriving vehicles. In addition to that, it is assumed that a power delivery rate of each pump in a certain tier is the same as a power acceptance rate of each vehicle in this tier. The total numbers of pumps in each tier ($\mathrm{Pump}_1, \mathrm{Pump}_2, \dots, \mathrm{Pump}_N$) are defined based on a currently known traffic pattern, which is a high level decision (see FIGURE 29). A concept of sharing pumps has been utilized in the definition of pump selection rule [29]. According to this concept, pumps in each tier are divided into sharable and designated. Designated pumps can be used for charging of same tier vehicles only. Due to a current state of battery technology, sharable pumps of a certain tier can be utilized for charging vehicles of lower tiers only. Besides, the following priority sequence (from highest to lowest) is used for charging pump selection: designated pumps of the same tier, sharable pumps of the same tier, sharable pumps of next highest tier, etc. Thus, highest tier vehicles can be charged at the highest tier pumps only; second highest tier vehicles can be charged at the second highest tier pumps and the highest tier pumps if none of second highest tier pumps is available and so on. The lowest tier vehicles can be charged by sharable pumps of all other tiers selected in a descending order. At the same time, the lowest tier pumps cannot be shared.

In the queueing and scheduling phase (see FIGURE 31), the defined parameters of charging station's operation: number of rejections and pumps' utilization (see section 5.2.2) are reported as final results. In addition to these results, the scheduling calendar (see FIGURES 50 and 51) displaying the timeline of each pump's utilization and the total load profile showing power consumption (see FIGURES 52 and 53) during the simulated operation time are provided during this phase. "Reject & referral" concept is considered to be applied for all vehicles that have not been queued based on their scheduling results. According to this concept, the service requests from such vehicles will be directed to the other charging stations connected to the current (or the neighboring) smart grid. At these charging stations, the requesting vehicles can be queued following the same online scheduling procedure. Such "reject & referral" concept can increase the efficiency of energy resources utilization and improve sustainability during arrivals' congestions.

As an example, the current implementation of online scheduling procedure has been coded in Matlab™ and Gurobi optimization solver has been called to solve a mixed-integer linear program. In addition to that, several simulation scenarios have been developed to demonstrate the example of charging station's operation depending on a decision about the number of sharable pumps in each tier, which belongs to the medium level decision-making hierarchy of autonomous charging station architecture.

5.3.2 Simulation scenarios

According to the developed analytical platform, simulation scenarios have been defined by assignment of arrival parameters during vehicle initialization (FIGURE 32).

Considering traffic patterns to the existing gas stations in urban areas [241], average arrival rates (λ) of 10 veh/hour, 12 veh/hour, and 14 veh/hour have been chosen for simulations. The arrival rate of 10 veh/hour has been set as a baseline representing a currently known traffic pattern. Whereas, 12 veh/hour and 14 veh/hour arrival rates have been chosen to reflect a possible future growth in vehicles' population in a given area. To satisfy the requirements for steady state arrival process, the maximum number of vehicles simulated ($\mathrm{Veh}_{\mathrm{max}}$) is considered to be 1000. In this case, the duration of simulation for baseline scenario is about 100 hours. Based on the information about the most popular types of electric vehicles in the US, three tiers of vehicles have been considered as a general case [29]. The corresponding charging parameters for each tier vehicles are provided in TABLE 14. It is assumed that a charging rate of each pump in a tier is equal to the power acceptance rate of the vehicles in the same tier.

TABLE 14: Charging parameters of three considered tiers

Tier	Battery size, kWh	Power acceptance rate, kW
1	81	120
2	20	6.6
3	14	3.3

Based on the average annual sales of the most popular in the US electric vehicles [23, 242], the ratios of them belonging to tiers 1, 2, and 3 are approximated as 0.2, 0.3, and 0.5 respectively. These vehicle tier ratios are considered as a balanced scenario for all chosen arrival rates. Besides, the combination of these vehicle tier ratios with the baseline arrival rate of 10 veh/hour along with service rate per pump in each tier has been used to calculate the number of pumps in each tier for a well-balanced condition between arrival and service rates at the charging station: $\frac{\lambda_i}{\mu_i} \sim 0.8$ [243] as shown in TABLE 15. In this case, λ_i and μ_i denote arrival and service rates in tier i respectively. In this calculation, energy requirements for electric vehicles in each tier are considered to be 80% of the average battery capacity for this tier shown in TABLE 14. An example of the calculations performed for tier 1 is provided below.

TABLE 15: Average charging time and rate in each tier

Tier	Average charging time per vehicle, hours	Service rate per pump, veh/hour	Number of pumps	Pump ID
1	0.54	1.85	2	1, 2
2	2.42	0.413	9	3, 4, …, 11
3	3.39	0.295	21	12, 13, …, 32

Since the battery size for tier 1 vehicles is 81 kWh, the average energy requirement for each vehicle in this tier is $0.8 \cdot 81 = 64.8$ kWh. For balanced scenario, arrival rate in tier 1 can be calculated as $\lambda_1 = 0.2 \cdot 10 = 2$ veh/hour. Hence, the required service rate in tier 1 can be calculated as $\mu_1 = \lambda_1/0.8 = 0.8 \cdot 2 = 2.5$ veh/hour. Therefore, the overall power delivery rate in tier 1 required for well-balanced condition is $2.5 \cdot 64.8 = 162$ kW, which can be supplied by 2 pumps of the first tier. Similar calculations have been performed to define the number of pumps in tiers 2 and 3 for a well-balanced condition. After that, all pumps have been assigned their pump IDs for convenience. The corresponding results are presented in TABLE 15. Being a high level decision (see FIGURE 29), the calculated number of pumps in each tier is the same for all considered scenarios.

After the number of pumps in each tier has been calculated, their selection order should be defined for different number of sharable pumps in tiers 1 and 2. Since tier 3 is the lowest tier for

TABLE 16: Pump selection order for chosen sharing combinations

Sharing combination	Sharable pumps		Pump selection order for given vehicle tier		
	Tier 1	Tier 2	Tier 1	Tier 2	Tier 3
1	0	0	1, 2	3, 4, …, 11	12, 13, …, 32
2	0	3	1, 2	4, 5, …, 11, 3	12, 13, …, 32, 3
3	0	3, 4, 5	1, 2	6, 7, …, 11, 3, 4, 5	12, 13, …, 32, 3, 4, 5
4	0	3, 4, …, 7	1, 2	8, 9, …, 11, 3, 4, …, 7	12, 13, … 32, 3, 4, …, 7
5	0	3, 4, …, 9	1, 2	10, 11, 3, …, 9	12, 13, … 32, 3, 4, …, 9
6	0	3, 4, …, 11	1, 2	3, 4, …, 11	12, 13, … 32, 3, 4, …, 11
7	1	0	2, 1	3, 4, …, 11, 1	12, 13, … 32, 1
8	1	3	2, 1	4, 5, …, 11, 3, 1	12, 13, … 32, 3, 1
9	1	3, 4, 5	2, 1	6, 7, …, 11, 3, 4, 5, 1	12, 13, … 32, 3, 4, 5, 1
10	1	3, 4, …, 7	2, 1	8, 9, …, 11, 3, 4, …, 7, 1	12, 13, … 32, 3, 4, … 7, 1
11	1	3, 4, …, 9	2, 1	10, 11, 3, …, 9, 1	12, 13, … 32, 3, 4, …, 9, 1

12	1	3, 4, …, 11	2, 1	3, 4, …, 11, 1	12, 13, … 32, 3, 4, …, 11, 1
13	1, 2	0	1, 2	3, 4, …, 11, 1, 2	12, 13, … 32, 1, 2
14	1, 2	3	1, 2	4, 5, …, 11, 3, 1, 2	12, 13, … 32, 3, 1, 2
15	1, 2	3, 4, 5	1, 2	6, 7, …, 11, 3, 4, 5, 1, 2	12, 13, … 32, 3, 4, 5, 1, 2
16	1, 2	3, 4, …, 7	1, 2	8, 9, …, 11, 3, 4, …, 7, 1, 2	12, 13, … 32, 3, 4, … 7, 1, 2
17	1, 2	3, 4, …, 9	1, 2	10, 11, 3, …, 9, 1, 2	12, 13, … 32, 3, 4, …, 9, 1, 2
18	1, 2	3, 4, …, 11	1, 2	3, 4, …, 11, 1, 2	12, 13, … 32, 3, 4, …, 11, 1, 2

the defined scenarios, its pumps cannot be shared, i.e., all pumps in tier 3 are designated ones. The numbers of pumps that can be shared in tiers 1 and 2 are from 0 to 2 and from 0 to 9 respectively. Hence, there are 30 possible sharing combinations. It has been further noticed that a change in number of sharable pumps in tier 2 has a small effect on charging stations operation (see subsection 1.3.3). Therefore, 18 sharing combinations shown in TABLE 16 have been chosen for simulation experiments to reduce the computation time. For each vehicle tier, pump selection order has been defined based on pump sharing concept described in subsection 1.3.1 (see TABLE 16).

Various data analytics approaches can be applied to obtain an accurate information about vehicle tier ratios for any particular location of a certain charging station. Hence, balanced scenario has been considered to address the case when data analytics provided accurate results. Otherwise, it is possible that arrival rates of certain tiers can be underestimated or overestimated due to inaccurate data analytics results. To investigate the performance of charging station's operation when the arrival rates of vehicles are changing (e.g., underestimated or overestimated) in different tiers, we experimented with increasing and decreasing the tier 1 arrival rate by 10% with the opposite change in the arrival rate of tier 2, while keeping the same arrival rate for tier 3. This results in three different settings for vehicle ratios in tiers 1, 2, and 3: 0.2, 0.3, 0.5; 0.1, 0.4, 0.5; and 0.3, 0.2, 0.5 as shown in TABLE 17. While the first setting is defined as the balanced scenario, the second and third settings are defined as the lower first tier (LFT) and the higher first tier (HFT) scenarios.

TABLE 17: Considered scenarios based on vehicle ratios per tier

Tier	Balanced	Lower first tier	Higher first tier
1	0.2	0.1	0.3
2	0.3	0.4	0.2
3	0.5	0.5	0.5

For the sharing pump combinations shown in TABLE 16, the following parameters have been calculated for the selected arrival rates (10 veh/hour, 12 veh/hour, and 14 veh/hour) and vehicle tier ratios (balanced, lower first tier, and higher first tier):

- Number of rejected vehicles (overall and per tier) out of 1000 arrivals;
- Utilization of pumps (overall and per tier).

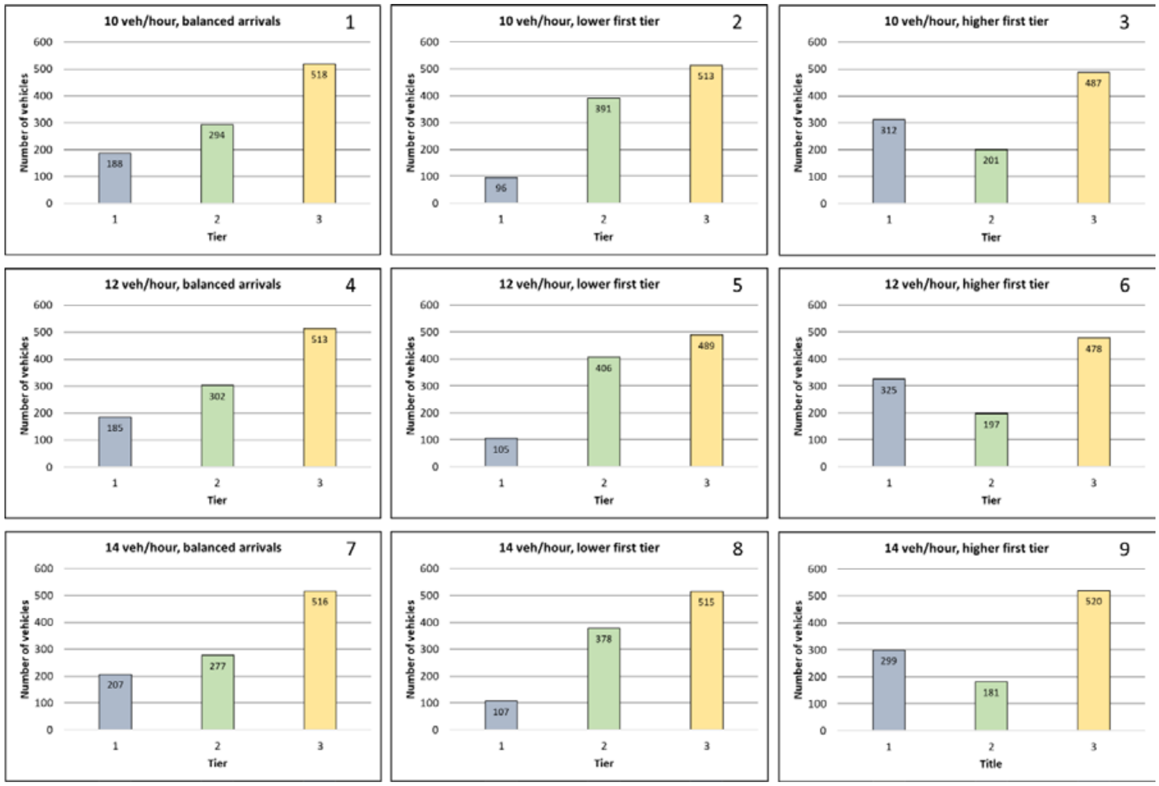

FIGURE 32: Simulation experiments based on developed scenarios

According to the developed simulation scenarios, nine experiments have been conducted (see FIGURE 32). In these experiments, the arrival rates of 10 veh/hour, 12 veh/hour, and 14 veh/hour are considered in combination with each vehicle tier ratio shown in TABLE 17. The dependence of number of rejected vehicles out of 1000 arrivals and utilization of pumps, both overall and per tier, has been analyzed for each number of sharable pumps defined in TABLE 16. Thus, experiments 1, 2, and 3 are conducted for 10 veh/hour arrival rate with balanced, LFT, and HFT vehicle tier ratios. Whereas, experiments 4, 5, 6 and 7, 8, 9 are conducted for 12 veh/hour and 14 veh/hour arrival rates respectively in combination with the same vehicle tier ratios.

5.3.3 Experimental results and analysis

The obtained results from the conducted simulation experiments are provided in FIGURES 33 – 50, where the FIGURES with odd numbers illustrate the number of rejections out of 1000 arrivals and FIGURES with even numbers illustrate the corresponding utilization of pumps. Due to a relatively large number of results, a specific numbering of them has been placed in the upper right corner of each figure for convenience. The number before decimal point changing from 1 to 9 indicates the number of simulated experiment in accordance with FIGURE 32. Whereas, numbers “1” and “2” after decimal point are utilized for the parts describing the number of rejections and pump utilization results respectively. In addition to that, tier-specific results of each part of simulated experiment are labeled with letters “a”, “b”, and “c” corresponding to sharing of 0, 1, and 2 pumps of tier 1 respectively.

The obtained results can be used to draw conclusions about operational performance of the selected design of charging station under the specified scenarios. As expected, sharing of pumps for balanced scenario is not beneficial for neither reduction of number of rejections nor for increasing of charging pumps’ utilization. The observed reduction in the number of rejections and corresponding increase in pumps’ utilization have been occurred due to a randomness of arrival process and can be considered as negligible.

Sharing of tier 1 pumps has higher impact on both, number of rejections and pump utilization, than sharing of tier 2 pumps. Sharing of both pumps of tier 1 results in the highest number of rejections increasing it by 8 to 25 vehicles with respect to a non-shared scenario and in highest pump utilization increasing it by 5% to 6% with respect to a non-shared scenario (compare FIGURES 33 and 39). Whereas, sharing of only one pump in tier

1 results in lowest number of rejections reducing it by 5 to 8 vehicles with respect to a non-shared scenario (see FIGURES 39 and 45). It can also be noticed that sharing of up to 5 pumps in the second tier reduces the overall number of rejections (see FIGURE 39). Otherwise, the number of rejections will also depend on the number of pumps shared in tier 1.

On one side, sharing of one and two pumps in tier 1 increases the number of overall rejections by about 35 and 50 vehicles respectively with respect to non-shared scenario. On the other side, it increases the overall pump utilization by about 6% (see FIGURE 32). Besides, sharing of up to 3 pumps in the second tier reduces the number of overall rejections by about 3% allowing to increase pump utilization by about the same amount. Whereas, sharing of more than 3 pumps in tier 2 increases the number of overall rejections and reduces pump utilization (except with for a non-shared scenario when the utilization stays constant).

The results for overall pump utilization are used to obtain the information about power consumption within a designed charging station. Based on power delivery rates of charging pumps and their quantity in each tier (power acceptance rate of same tier vehicle shown in TABLE 14), the maximum power consumption from the energy grid in tiers 1, 2, and 3 (e.g., for 100% utilization of the specific tier) for the considered design of charging station are 240 kW, 59.4 kW, and 69.3 kW respectively. Whereas, the total power consumption (corresponding to 100% utilization) for the considered design of charging station is 368.7 kW. Dependence of the total and tier specific power consumption on the number of shared pumps in tiers 1 and 2 for specified arrival scenarios follows the same trend as pumps' utilization and is shown at even numbers of FIGURES 33 – 50.

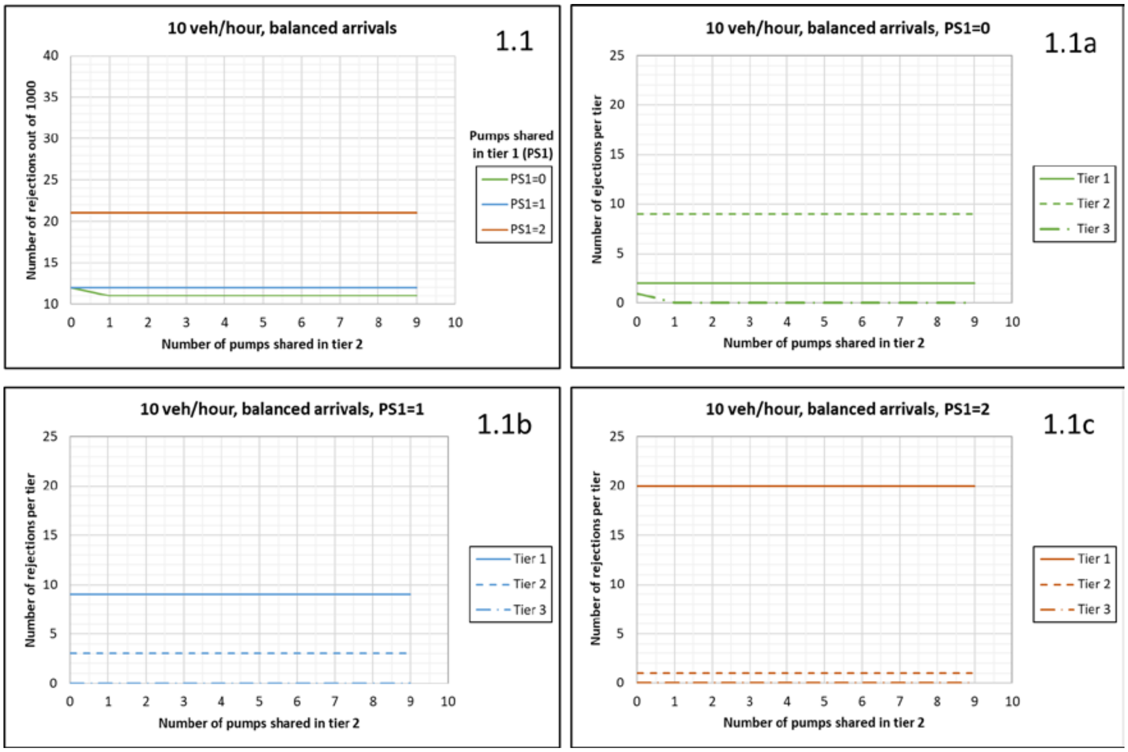

FIGURE 33: Number of rejections out of 1000 arrivals for 10 veh/hour arrival rate with balanced vehicle ratio vs number of pumps shared in tiers 1 (PS1) and 2.

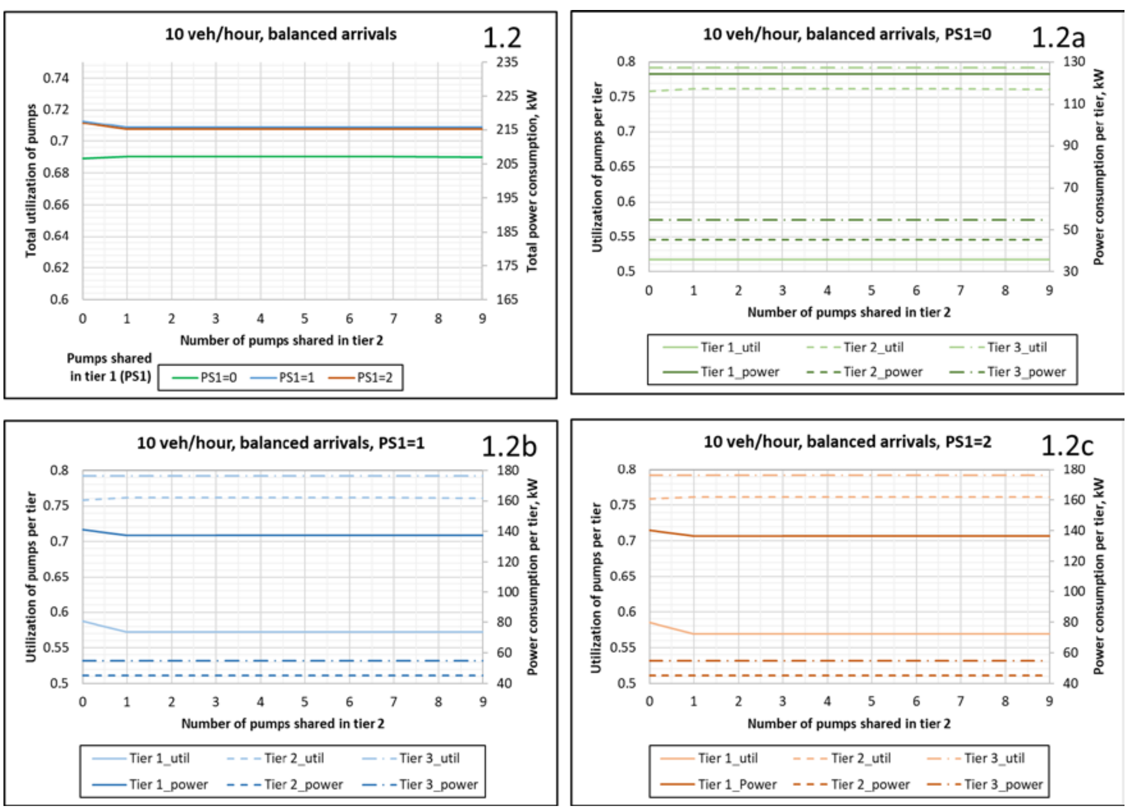

FIGURE 34: Utilization of pumps for 10 veh/hour arrival rate with balanced vehicle ratio vs number of pumps shared in tiers 1 (PS1) and 2.

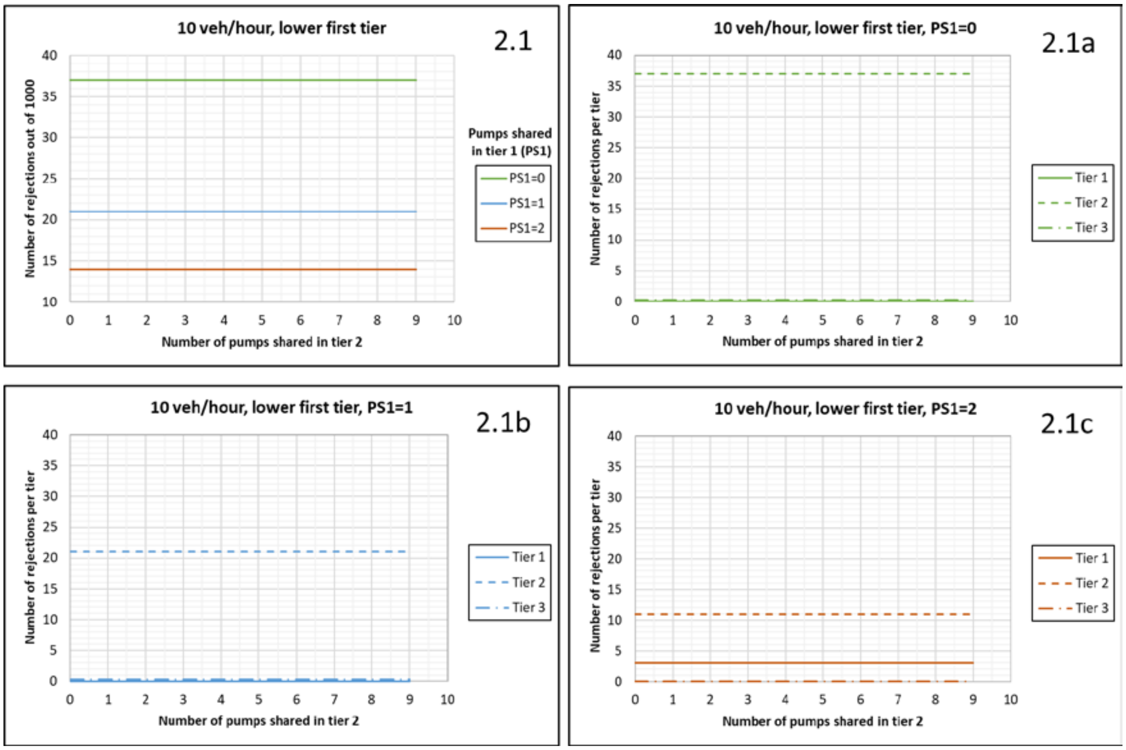

FIGURE 35: Number of rejections out of 1000 arrivals for 10 veh/hour arrival rate with lower first tier vehicle ratio vs number of pumps shared in tiers 1 (PS1) and 2.

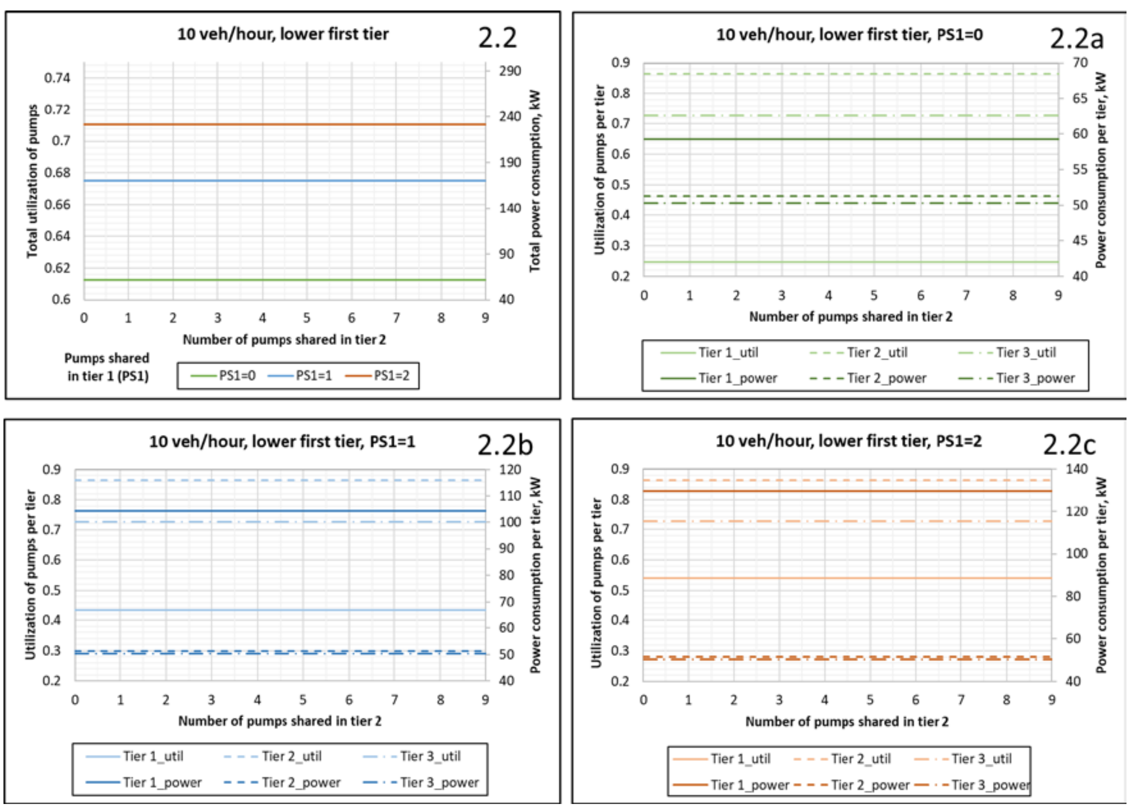

FIGURE 36: Utilization of pumps for 10 veh/hour arrival rate with lower first tier vehicle ratio vs number of pumps shared in tiers 1 (PS1) and 2.

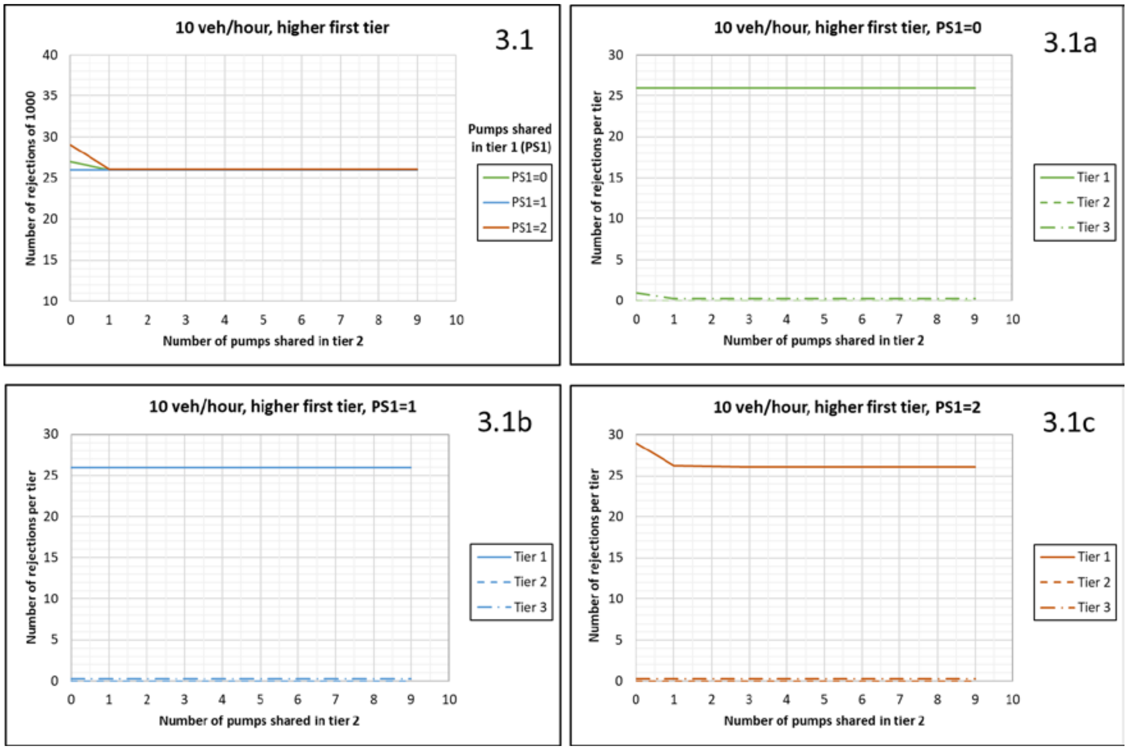

FIGURE 37: Number of rejections out of 1000 arrivals for 10 veh/hour arrival rate with higher first tier vehicle ratio vs number of pumps shared in tiers 1 (PS1) and 2.

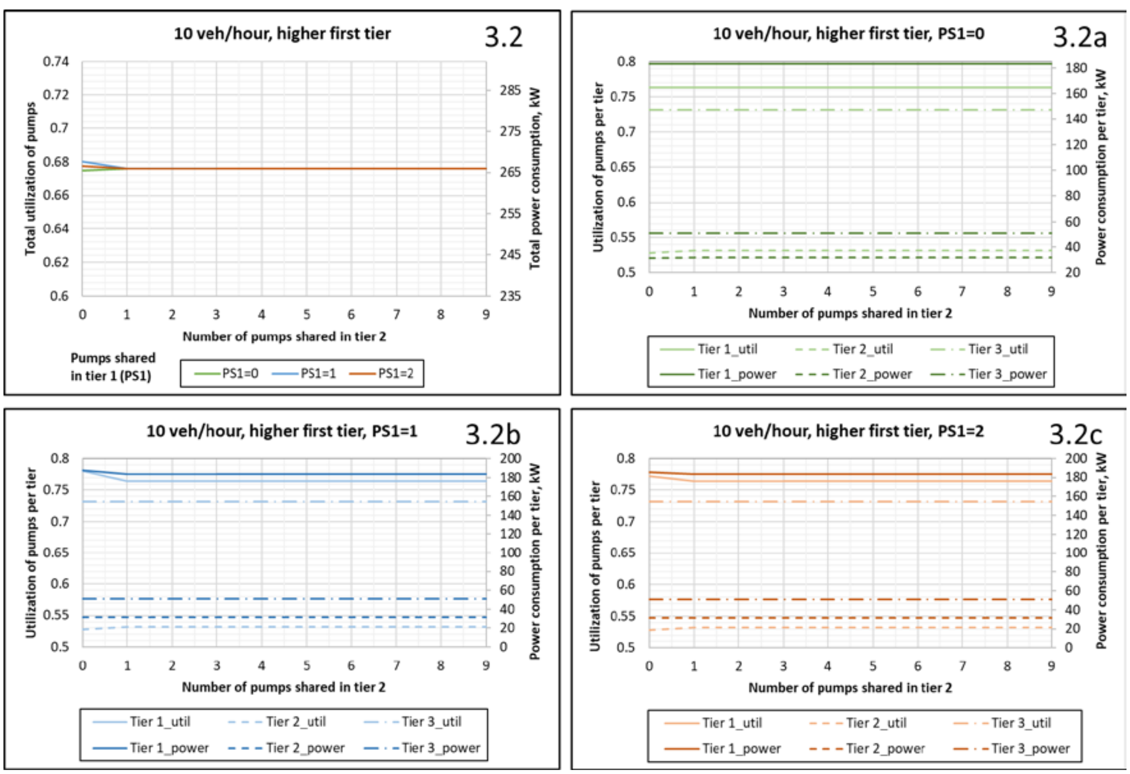

FIGURE 38: Utilization of pumps for 10 veh/hour arrival rate with higher first tier vehicle ratio vs number of pumps shared in tiers 1 (PS1) and 2.

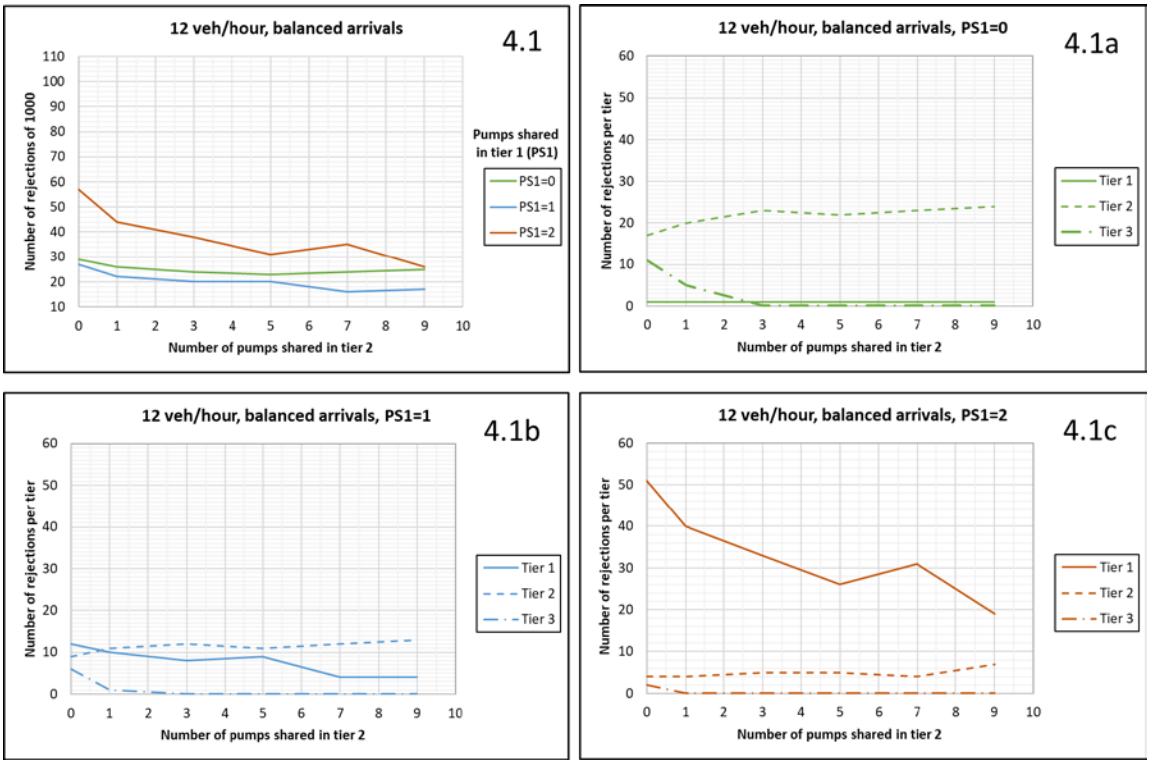

FIGURE 39: Number of rejections out of 1000 arrivals for 12 veh/hour arrival rate with balanced vehicle ratio vs number of pumps shared in tiers 1 (PS1) and 2.

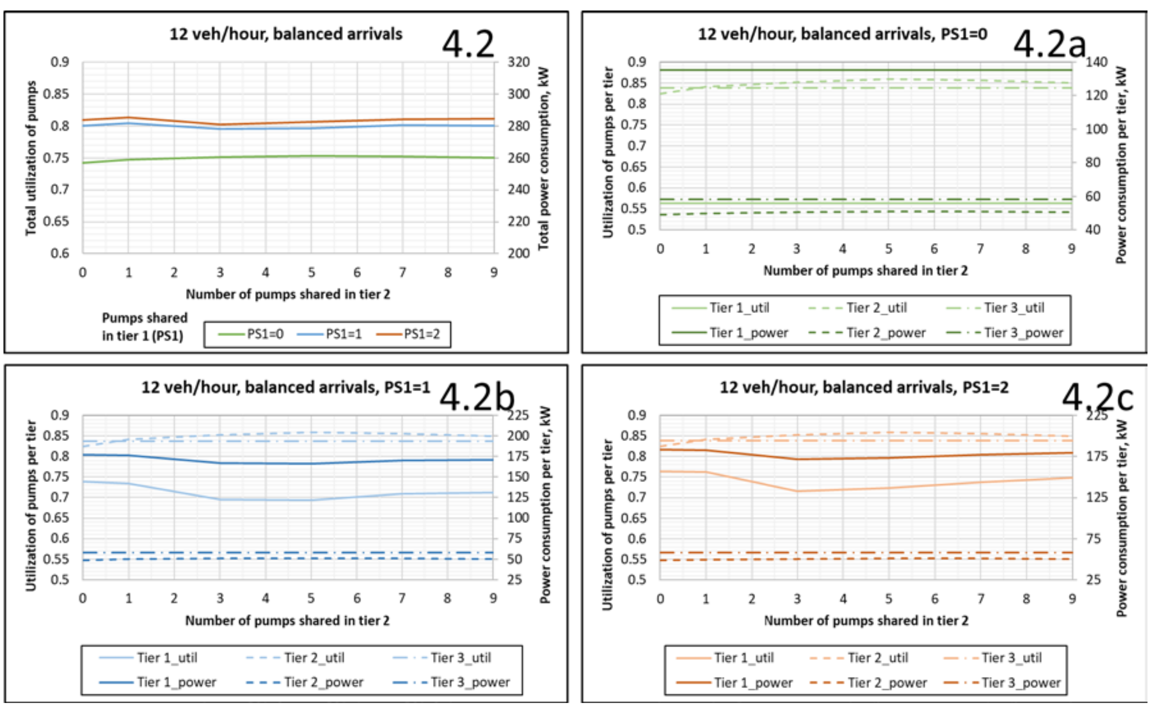

FIGURE 40: Utilization of pumps for 12 veh/hour arrival rate with balanced vehicle ratio vs number of pumps shared in tiers 1 (PS1) and 2.

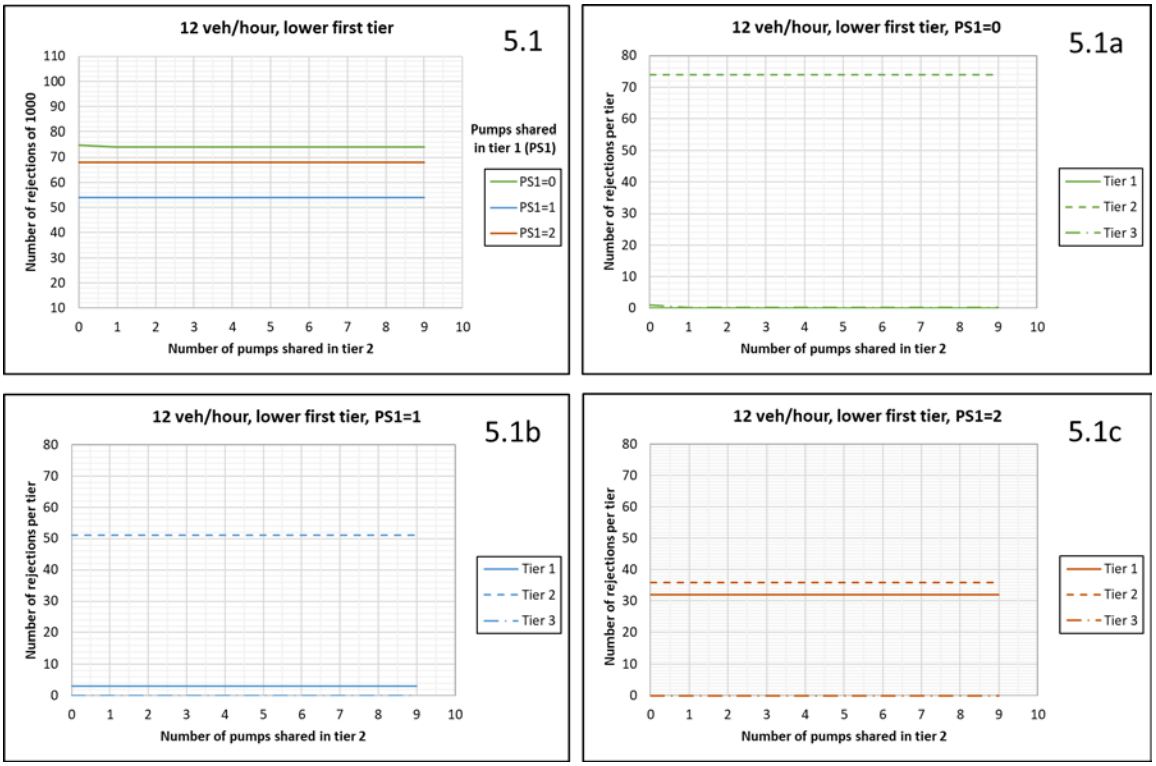

FIGURE 41: Number of rejections out of 1000 arrivals for 12 veh/hour arrival rate with lower first tier vehicle ratio vs number of pumps shared in tiers 1 (PS1) and 2.

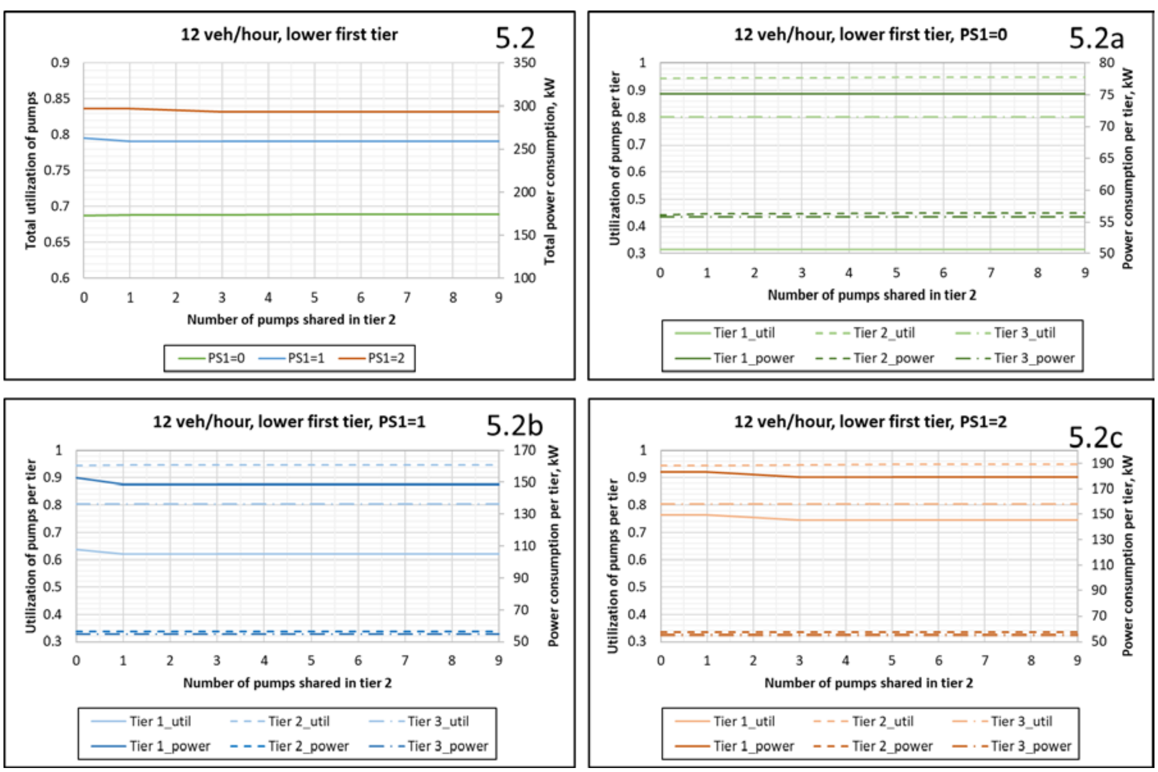

FIGURE 42: Utilization of pumps for 12 veh/hour arrival rate with lower first tier vehicle ratio vs number of pumps shared in tiers 1 (PS1) and 2.

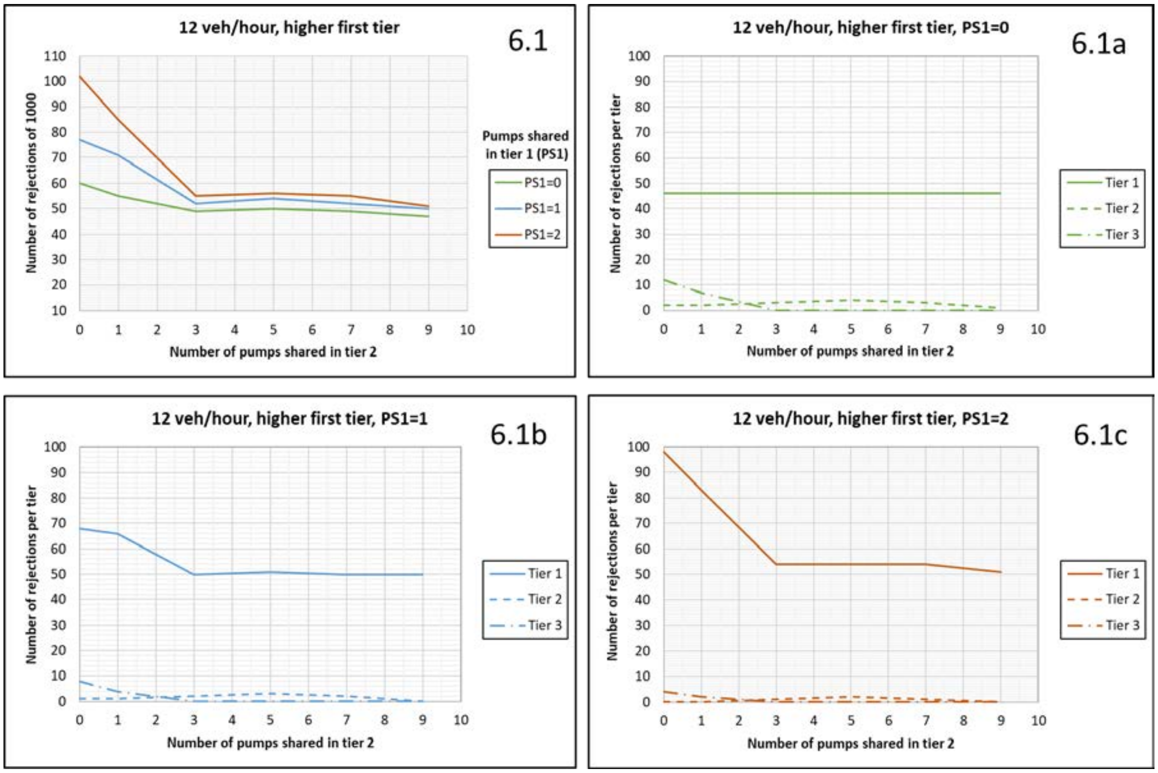

FIGURE 43: Number of rejections out of 1000 arrivals for 12 veh/hour arrival rate with higher first tier vehicle ratio vs number of pumps shared in tiers 1 (PS1) and 2.

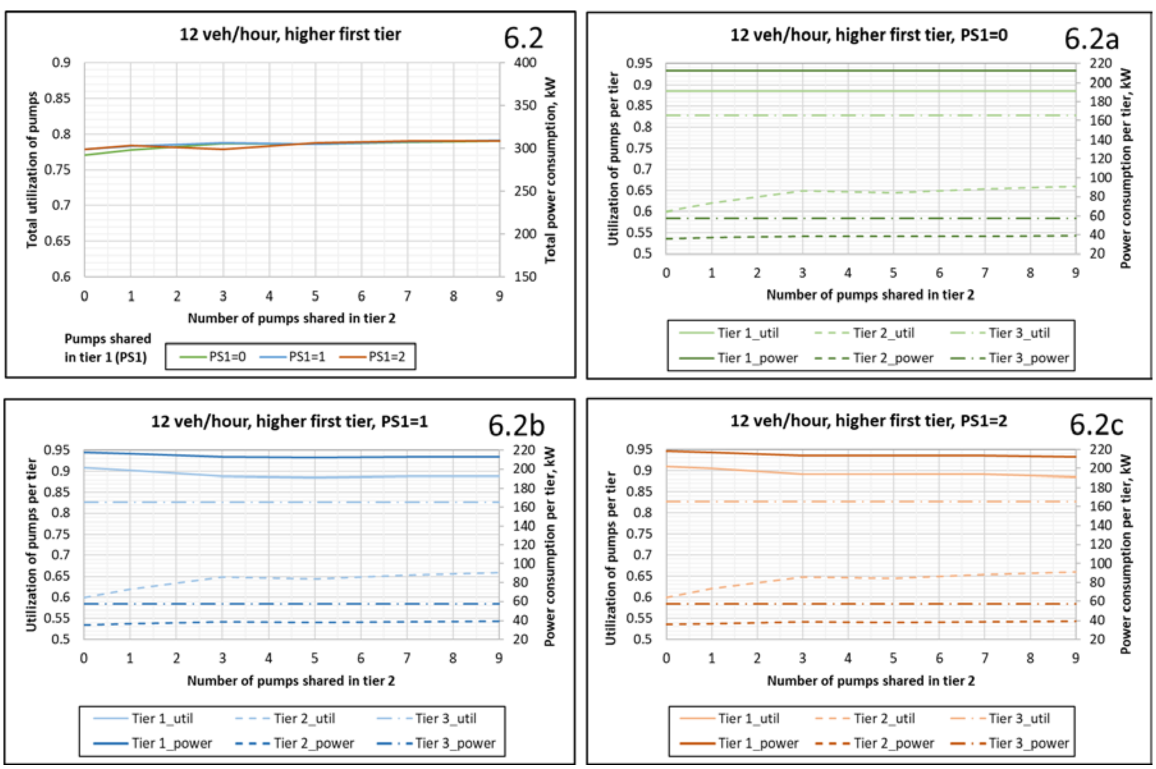

FIGURE 44: Utilization of pumps for 12 veh/hour arrival rate with higher first tier vehicle ratio vs number of pumps shared in tiers 1 (PS1) and 2.

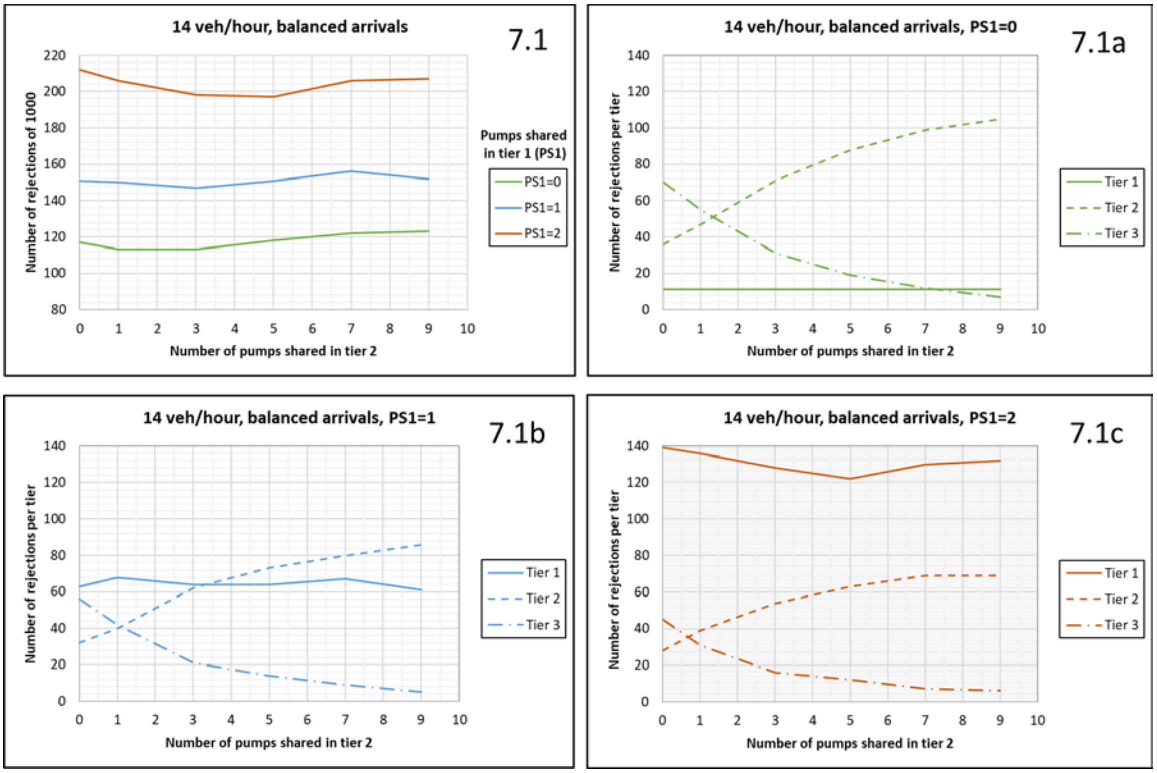

FIGURE 45: Number of rejections out of 1000 arrivals for 14 veh/hour arrival rate with balanced vehicle ratio vs number of pumps shared in tiers 1 (PS1) and 2.

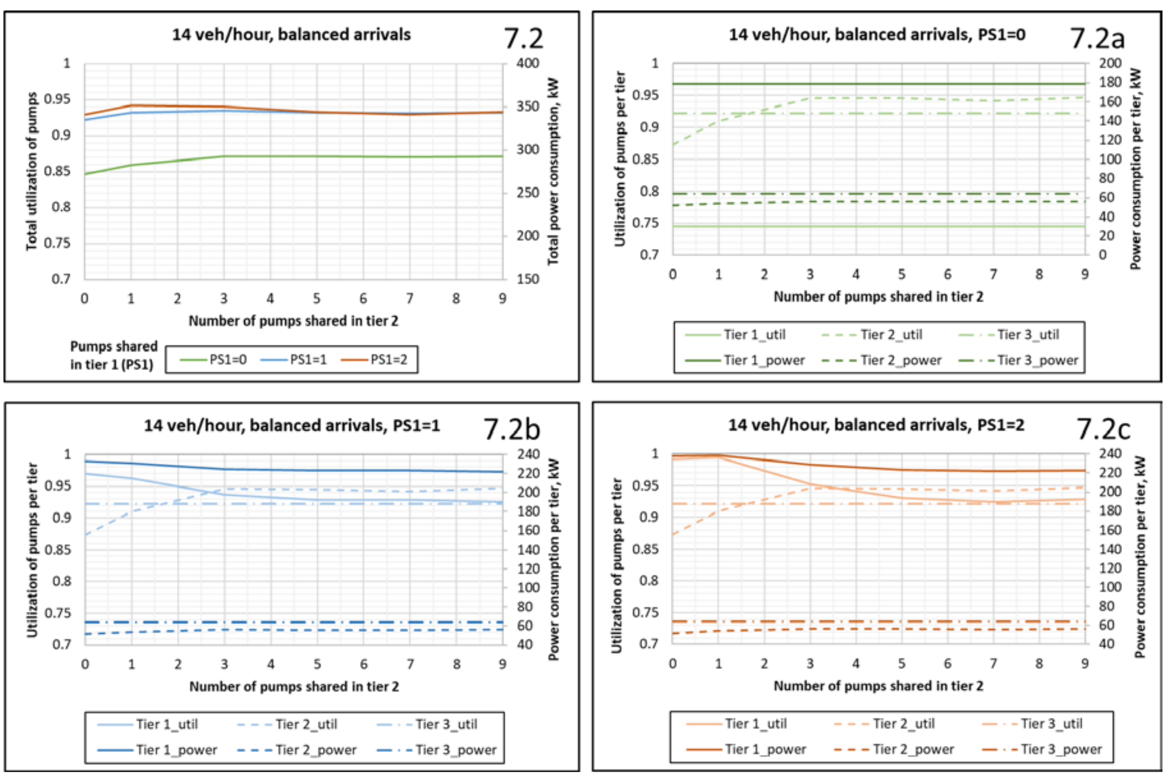

FIGURE 46: Utilization of pumps for 14 veh/hour arrival rate with balanced vehicle ratio vs number of pumps shared in tiers 1 (PS1) and 2.

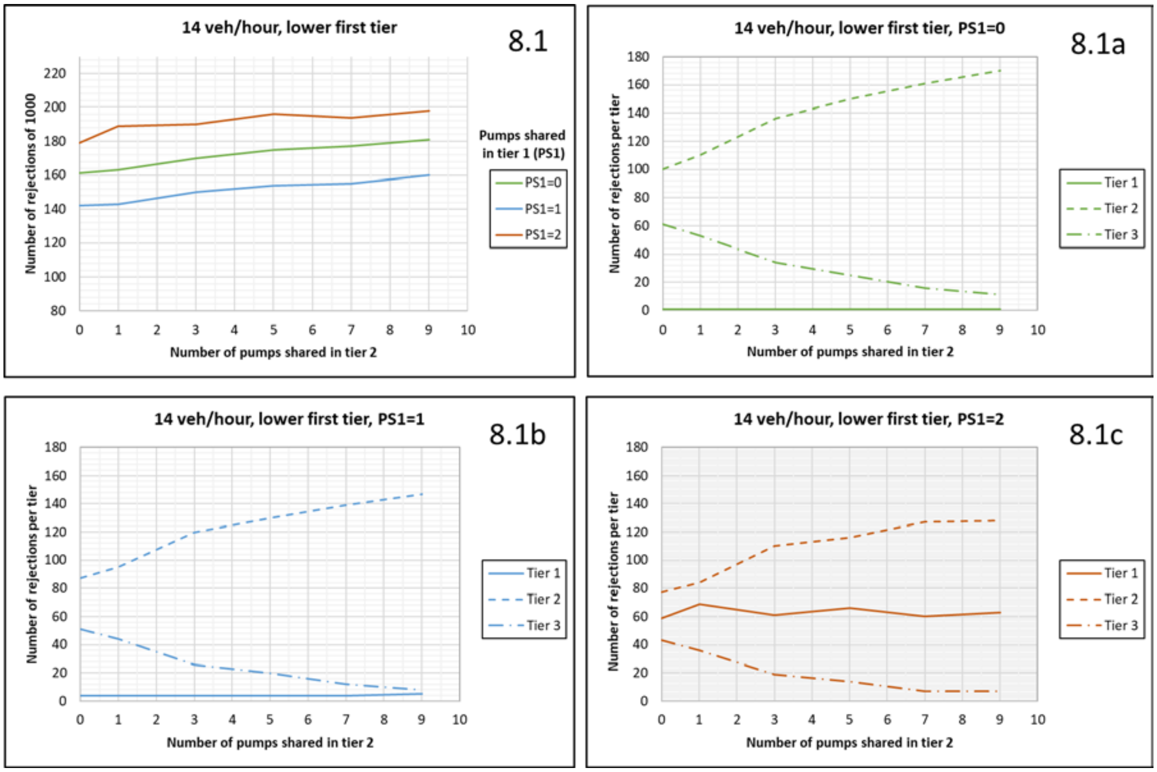

FIGURE 47: Number of rejections out of 1000 arrivals for 14 veh/hour arrival rate with lower first tier vehicle ratio vs number of pumps shared in tiers 1 (PS1) and 2.

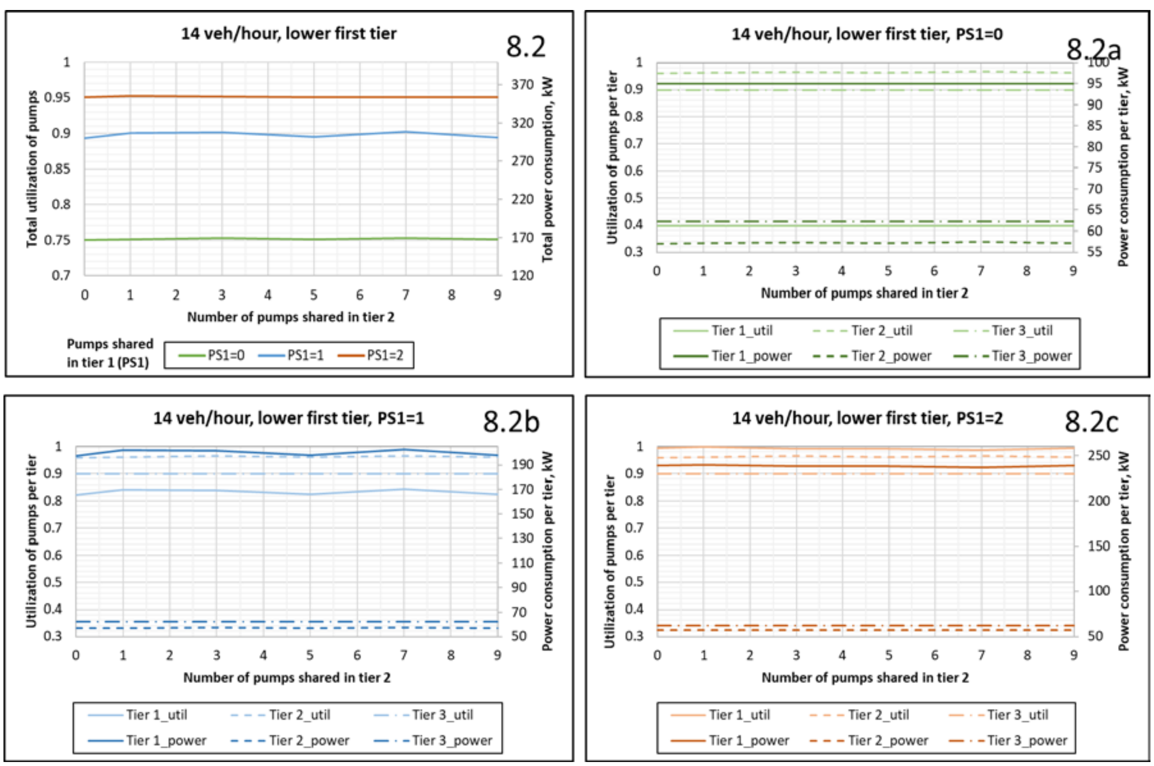

FIGURE 48: Utilization of pumps for 14 veh/hour arrival rate with lower first tier vehicle ratio vs number of pumps shared in tiers 1 (PS1) and 2.

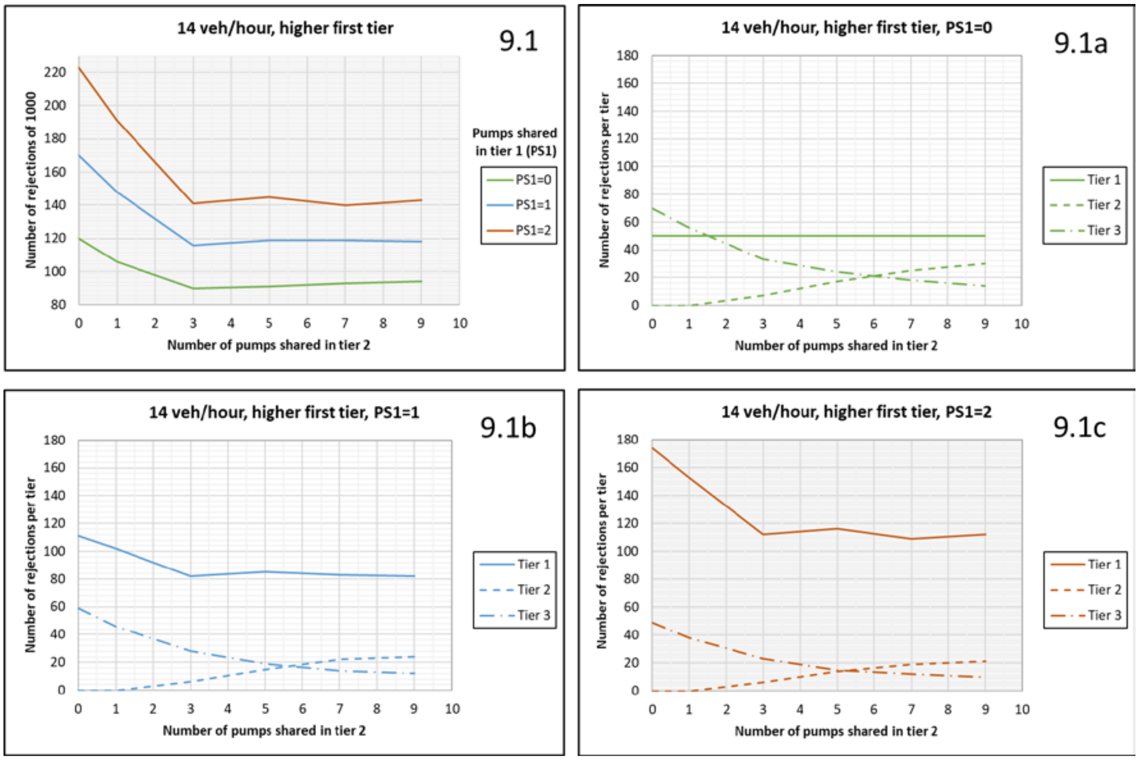

FIGURE 49: Number of rejections out of 1000 arrivals for 14 veh/hour arrival rate with higher first tier vehicle ratio vs number of pumps shared in tiers 1 (PS1) and 2.

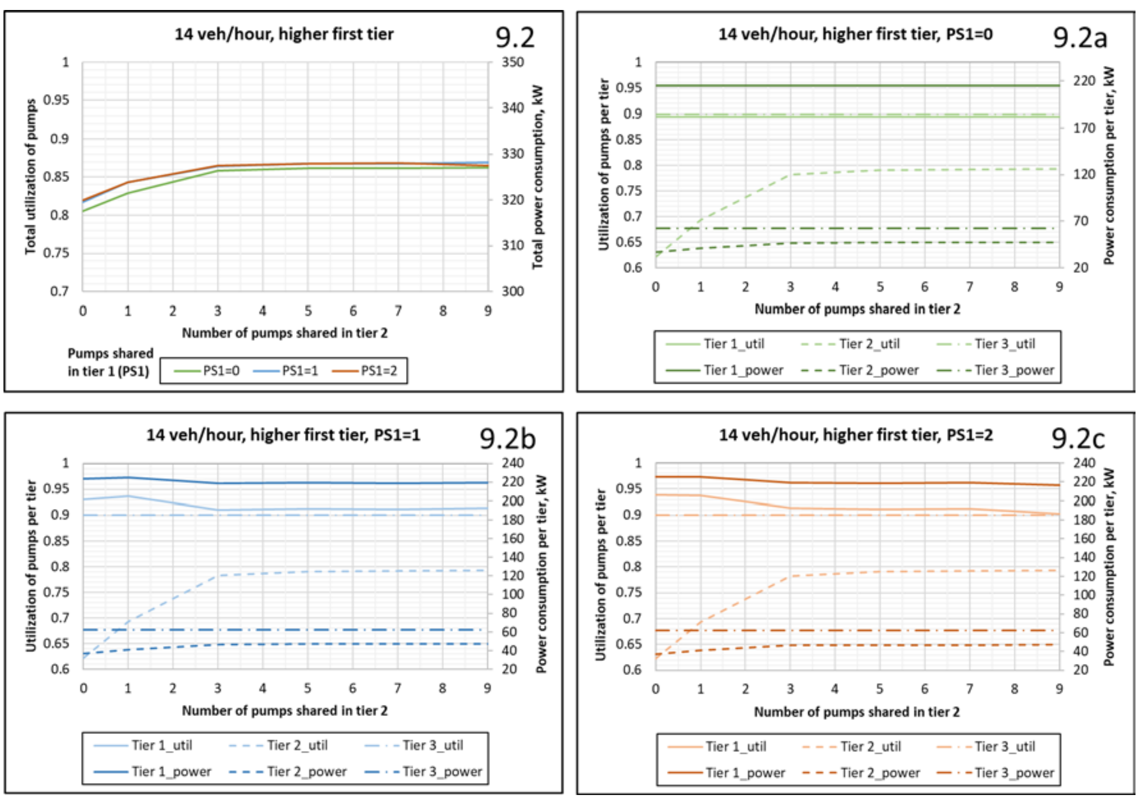

FIGURE 50: Utilization of pumps for 14 veh/hour arrival rate with higher first tier vehicle ratio vs number of pumps shared in tiers 1 (PS1) and 2.

It can be observed from FIGURE 33 that sharing of one pump in tier 1 allows to increase the utilization of tier 1 pumps by up to 18% with a corresponding increase in number of rejections by 3 vehicles with respect to a non-sharing scenario. Whereas, sharing of two pumps in tier 1 results in a highest number of rejections in this tier increasing it by at least 19 vehicles with respect to a non-shared scenario and 15 vehicles with respect to sharing of one tier 1 pump. At the same time, sharing of 2 pumps in tier 1 increases the utilization of tier 1 pumps by about 2% only with respect to the scenario of sharing just one pump in tier 1. It can also be observed that sharing of tier 2 pumps provides a trade-off between an increase in number of rejections in tier 2 and a decrease in number of rejections in tier 3 and allows to increase the utilization of tier 2 pumps by about 3%.

It can be observed from FIGURE 34 that sharing of one pump in tier 1 allows to increase the utilization of tier 1 pumps by about 22% with a corresponding increase in number of rejections by 52 vehicles with respect to a non-sharing scenario. Whereas, sharing of two pumps in tier 1 results in a highest number of rejections in this tier increasing it by at least 110 vehicles with respect to a non-shared scenario and 60 vehicles with respect to sharing of one tier 1 pump. At the same time, sharing of 2 pumps in tier 1 increases the utilization of tier 1 pumps by about 2% only with respect to the scenario of sharing just one pump in tier 1. It can also be observed that sharing of tier 2 pumps provides a trade-off between an increase in number of rejections in tier 2 and a decrease in number of rejections in tier 3 and allows to increase the utilization of tier 2 pumps by about 8%.

As indicated scheduling calendar illustrating the timeline of each pump’s utilization is shown at FIGURES 50 and 51. Each line of this calendar shows the ordered sequence of time intervals when the corresponding vehicles have been scheduled at the particular charging pump based on the information obtained from V_{aggr} matrix (see section 5.3.1). Recall that the default online scheduling problem considers minimizing the total completion times [5]. This platform can alternatively consider the makespan as its objective function. It has been noticed that the application of sum of weighted completion times as an objective function results in several additional empty time slots (non-utilized for charging) with respect to the utilization of makespan as an objective function (FIGURE 50).

It can be observed from even numbers of FIGURES 33 – 50 that first tier has the highest contribution to the overall power consumption for all types of traffic patterns and pump sharing scenarios. Whereas, the contribution of tier 2 is close to the one of tier 3. In spite of the fact that the maximum power consumption for chosen design of charging station is higher for tier 3 than for tier 2, pump utilization rate should be taken into a consideration, which depends on a particular traffic profile. The presented graphs (even numbers of FIGURES 33 – 50) illustrate the dependence of charging station's power consumption on the number of sharable pumps in each tier can be analyzed using the developed platform.

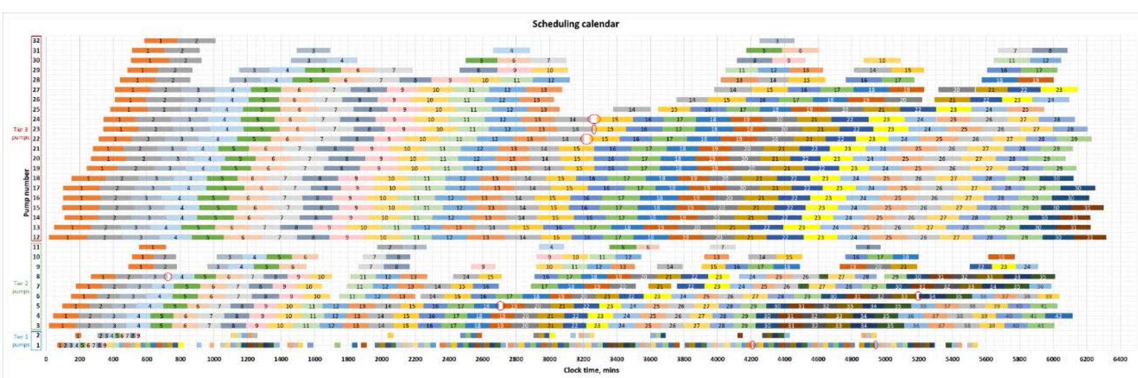

FIGURE 51: Scheduling calendar when sum of weighted completion times is used as the objective function. Highlighted in red empty time slots are not presented when makespan is utilized as the objective function (see FIGURE 52)

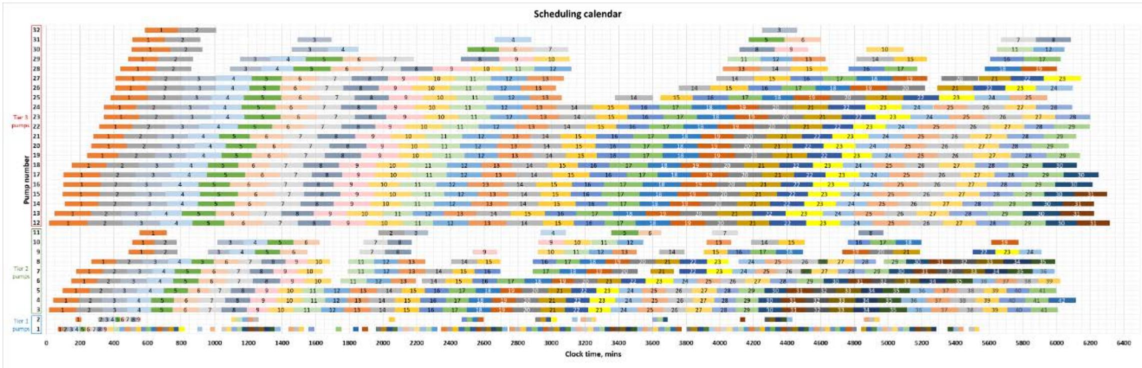

FIGURE 52: Scheduling calendar when makespan is used as the objective function.

Power consumption profiles for arrival rates of 10 veh/hour and 12 veh/hour with BAR and charging station's design with non-sharable pumps are shown at FIGURES 53 and 54. The shapes of these profiles are purely defined by the corresponding traffic pattern and a certain design of charging station (number of charging pumps in each tier), which also determines its maximum capacity (see FIGURES 53 and 54). Largest increases and decreases in power consumption correspond to the moments of connections and disconnections of tier 1 vehicles to their charging pumps. Due to significant difference in charging rates between tier 1 and tiers 2 and 3, similar connections and disconnections of vehicles belonging to last two tiers result in considerably smaller increases and decreases of power consumption profile. On one side, such profile is utilized to estimate the requirements for energy generation. On the other side, it is used for energy consumption management, e.g., reduction of peak-to-average ratio, shifting of energy load from peak to off-peak hours, etc.

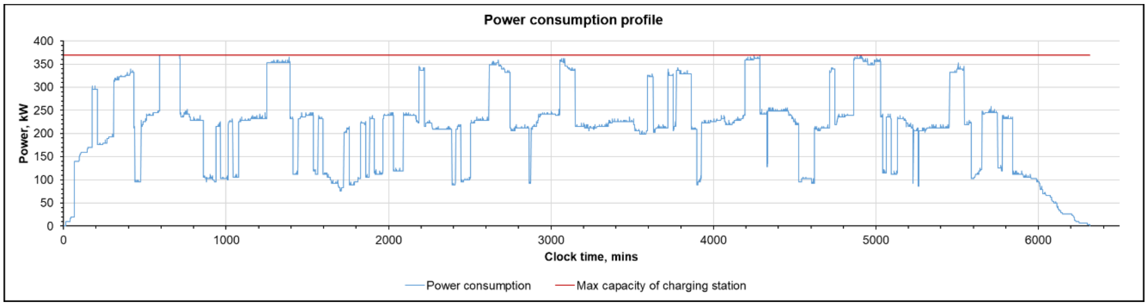

FIGURE 53: Power consumption profile for arrival rate of 10 veh/hour with BAR and charging station's design with non-sharable pumps only.

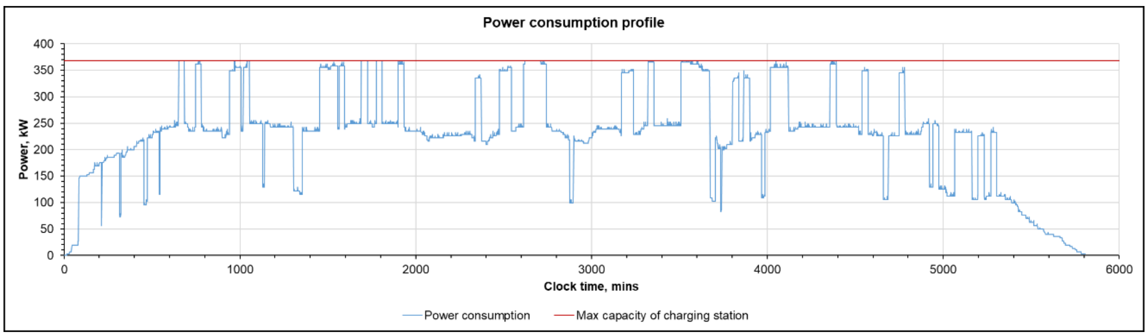

FIGURE 54: Power consumption profile for arrival rate of 12 veh/hour with BAR and charging station's design with non-sharable pumps only.

Several general observations and recommendations can be stated from the results obtained for overall number of rejected vehicles and overall utilization of pumps:

1. Sharing of pumps for balanced arrival rate (i.e., 10 veh/hour) and corresponding distribution, is not beneficial for reduction of vehicles' rejection and increasing of pumps' utilization (FIGURE 32 and FIGURE 33).
2. Low level of overall share, e.g., about 30% of pumps in tiers 1 and 2, can be recommended for most of scenarios as the most robust design for reduction of the overall number of rejections and pump utilization. However, if the arrival distribution of a certain tier is higher than expected, sharing of pumps in this tier is not recommended. For example, scenarios with zero sharable pumps in tier 1

produce least number of rejections for any arrival rate with a HFT arrival distribution.

3. Due to a big difference in charging rates between vehicles of tier 1 and vehicles of tiers 2 and 3, it is not recommended to share tier 1 pumps, unless the arrival rate for vehicles of this tier is lower than expected and the arrival rates of lower tiers are higher than expected. For example, sharing both pumps in tier 1 for 10 veh/hour arrival rate with LFT arrival distribution produces least number of rejections than non-sharing or partial sharing of tier 1 pumps. It can be observed from "Utilization of pumps per tier" graphs that such least number of rejections is achieved by a significant increase of tier 1 pumps' utilization from 0.247 to 0.541.
4. For any considered arrival rate, the overall utilization of pumps is the highest for the balanced arrival distribution if the overall level of share is low (about 30% of pumps in tiers 1 and 2).
5. For a non-balanced arrival distribution, e.g., LFT, the overall pump utilization is significantly increasing when the number of sharable pumps in under-utilized tier, e.g., tier 1 for LFT, is increasing for any considered arrival rate. The increase in overall pumps' utilization of 9.8%, 14.9%, and 20% has been observed for arrival rates of 10 veh/hour, 12 veh/hour, and 14 veh/hour, all with LFT arrival distribution, when the number of sharable pumps in tier 1 has been increased from 0, to 1 and 2 respectively.
6. A trade-off between minimizing the number of rejections and maximizing pumps' utilization can be observed. On one side, the number of rejections can be defined to achieve a required pumps' utilization in a given tier. On the other side, an

achievable pumps' utilization can be determined for an accepted number of rejections. The minimum number of overall rejections (11) can be achieved when the overall pumps' utilization is 69%. It occurs for a balanced condition in terms of distribution and arrival rate (10 veh/hour in our scenarios). When arrival rate increases to 14 veh/hour for the same arrival distribution, pay-off for the maximum pumps' utilization of 94% is about 210 rejections or 21% of all arrivals.

In addition, further observations can be stated from the analysis of results obtained for numbers of rejections and pump utilization of separate tiers:

1. For all considered arrival rates with balanced or HFT arrival distributions, the highest overall rejection rates correspond to the scenarios when only highest tier pumps (tier 1 in our scenarios) are shared. Hence, if all tiers are equally utilized, sharing should be started from with the lowest tier available. Otherwise, the underutilized tiers should be used first.
2. Since the lowest tier (tier 3 in our scenarios) cannot be used for sharing, its utilization cannot be increased. At the same time, the number of rejections in tier 3 can be significantly decreased using sharable pumps of tiers 1 and 2. This effect can be clearly observed for the scenario with an arrival rate of 14 veh/hour and balanced arrival distribution.
3. Since highest tier vehicles (tier 1 in our scenarios) cannot be charged by sharable pumps of any other tier, the initial rejection rate (i.e., corresponding to a non-sharing condition for any scenario) of this tier cannot be decreased by sharing.
4. In many scenarios, the observed reduction (or increase) of overall number of rejections has different effect on the rejections in a particular tier. Specifically, the

overall number of rejections can decrease while the number of rejections can increase in a certain tier and decrease or stay constant in the other tiers and vice versa. For example, sharing of both tier 1 pumps in LFT arrival distribution reduces the overall number of rejections. Similar effect can be observed for pumps' utilization in different tiers.

Since power consumption of a certain tier or pump is linearly proportional to its utilization parameter, all observations and recommendations stated above for pumps' utilization can be directly applied to analysis of power consumption. Such recommendations can lead to an implementation of dynamic energy distribution in automated charging station through a "dynamic pump sharing" concept. According to this concept, sharable pumps can be assigned for a certain time period during operation of charging station. For example, the time period of 1 hour can be considered for sharing. In this case, the developed model can be used to define the number of rejections and pumps' utilizations (both overall and for each tier) for the last hour along with the arrival rate in each tier. After that, the corresponding decisions can be made for sharing pumps in each tier. For example, if the arrival rates in given tiers decreased from the expected ones by a certain amount for the past hour, the number of shared pumps in these tiers should be increased by the required amount, which can be defined by either minimizing the number of rejections or maximizing the arrival rate decisions. Hence, the decisions about pumps' sharing can be made by data-driven approach.

The major features of the developed analytical platform are flexibility in initialization of vehicle arrival rate and tier distribution and scalability of energy consumption profiles of vehicles. As fast chargers (450 kWh, 550 kWh, etc.) become available, one can use this platform to perform various analyses of charging station's operation with state-of-the-art vehicles and chargers. Within such analyses, decisions can be made in the operational level so that the performance of the charging station can be optimized. In addition, the number of charging pumps can be optimized based on the traffic patterns of a certain area serviced by the analyzed charging station in the strategic level.

Moreover, this analytical platform can be applied at the multiple sites in a hierarchical way to analyze a network charging stations within a certain city, state, etc. On the other side, "scaling down" analysis can be performed. For example, feasibility of using single pump for services similar to Airbnb can be analyzed using this platform.

The other extension can be achieved by inclusion of pricing parameters, which can be based on such factors as time of charge, operating cost, generation cost, etc. The analysis on each of these factors can lead to the development of a dynamic pricing scheme that enables us to analyze the charging station from a business perspective.

The developed framework can be also extended by "opportunistic charging", "three-stage charging", and "reject & referral" approaches, which will be applied when a charging station is unable to service the initial request. The "opportunistic charging" approach considers utilization of two separate time slots for vehicle charging. In this case, a minimum threshold can be assigned for selection of such time slots, e.g., based on a tier or a certain percentage of the total charging time. The "three-stage charging" approach considers extension of charging process with two additional stages. In these stages, an extension of charging deadline and reduction of the required amount of energy can be offered to service a vehicle. "The reject and referral" approach can be utilized for a search of another charging station that can serve the initial request. Thus, application of these approaches can decrease the number of rejected vehicles and increase utilization of charging pumps, which in combination with an incentive pricing scheme will result in a more continuous load profile with a reduced number of kinks and valleys. From dynamic energy distribution point of view, such load profile will be a desirable feedback for energy generation domain.

The other extension can be achieved by inclusion of specific pricing parameters, which can be based on such factors as time of charge, operating cost, generation cost, etc. The analysis on each of these factors can lead to the development of a dynamic pricing scheme that enables us to analyze the charging station from a business perspective.

5.4 Summary

In this chapter, a secure resilient and safety critical architecture of autonomous charging station has been proposed. Leveraging an extensive work accomplished in the fields of robotics, queuing systems, optimization techniques, and other areas, the architecture consists of seven functional layers: Physical Infrastructure, Communication, Classification, Queueing, Financial, Services, and Multilayer Security. Functional operation of this architecture significantly relies on intelligent machine-to-machine and advanced sensing technologies. Communication layer is the key technological part of the developed architecture. The operation of the proposed charging station has been described by a servicing flow with the main focus on queueing and classification layers. The application of the proposed charging station in a dynamic energy distribution is enabled by a real-time energy consumption feedback provided by this station to energy generation domain.

An analytical framework has been developed to establish a robust architecture and describe the operation of the proposed charging station. This framework leverages the unsupervised AV's flexibility, stemming from their ability to travel to a charging/refueling station when they are not in use (especially during late night/early morning hours). Multi-level decision-making operation approach is utilized to describe the overall operation of autonomous charging station in this framework. Online scheduling has been applied at the operational level of decision-making. Estimation of its power consumption at any instance of operation is a key feature of the developed analytical framework.

A mathematical formulation and simulation implementation of the developed framework has been presented in an analytical platform. Several simulation experiments have been conducted to validate the developed analytical platform and demonstrate its application for analysis of charging station of operation at different levels of decision-making. The obtained observations show that the developed platform can be utilized to analyze the operation of autonomous charging station with a subsequent formulation of its operation rules.

In the developed platform, power consumption has been estimated in two ways. In the first way, the calculated tier and pump utilizations have been used in combination with their corresponding energy delivery rates. In the other way, the total load profiles of charging station have been calculated as a result of charging requests' processing at queueing and scheduling layers of the proposed architecture. Such load profiles can be further used to estimate the requirements for energy generation and energy consumption management, e.g., reduction of peak-to-average ratio, shifting of energy load from peak to off-peak hours, etc.

Due to the considered randomness of arrival process, the obtained results can illustrate the achievable performances under developed scenarios. These ideas can be verified through application of state-of-the-art scheduling algorithms and techniques. For example, the achievable performance can be different depending on what objective function is used. The objective function of the sum of weighted completion times has been used for all the conducted experiments. Several empty time slots can be observed on pumps' scheduling calendar when this objective function is applied (FIGURE 50). It can be beneficial to utilize the "opportunistic charging" approach for these time slots to serve walk-in vehicles. Alternatively, the objective function of makespan has been considered. Application of this objective function reduces the number of empty time slots and can be beneficial when a throughput of a certain pump needs to be increased (FIGURE 51).

Overall, the obtained results indicate that the demonstrated analytical platform can be used by businesses and stake holders to optimize the operation of their charging stations, e.g., by development of rules for dynamic pump sharing or profit-pricing models. For instance, these rules can be based on number of vehicles' rejections and pumps' utilization, i.e., the parameters of autonomous charging station's operation defined by the developed analytical platform. Such optimization of charging stations' operation will in turn improve efficiency of dynamic energy distribution through various approaches: dynamic pump sharing, opportunistic charging, three-stage charging, and reject and referral.

CHAPTER 6: DISCUSSION AND FUTURE RESEARCH

Application of flexible and secure M2M communication networks connecting a large number of sensors and actuators keep transforming SGs it into an intelligent electricity network. This intelligent electricity network is being enhanced with various advanced techniques such as dynamic demand management and dynamic estimation of energy generation and consumption, which can be performed in real-time on a continuous basis.

Dynamic load scheduling is another advanced technique that have been successfully developed and implemented based on underlying M2M communication network of a SG. Conveying benefits for multiple stakeholders of SGs, this technique has been extensively analyzed with various optimization approaches. The introduced opportunity of utilization of load profiles with high temporal sampling for dynamic load scheduling can increase sustainability and resilience of current SGs. This consequence is especially important for the SGs with a large number of critical energy loads in their user domains. In addition to that, the increased accuracy of the total load profile estimation achieved by the introduced opportunity can have considerable cumulative effect for future expansion of current SGs.

The proposed architecture of autonomous charging station is another application of dynamic energy distribution in SGs supported by M2M communication networks and intelligent sensing technologies. During its operation, the proposed charging station provides its real-time energy consumption as a feedback to its energy generation domain. Widespread deployment of unsupervised autonomous vehicles across the globe opens up significant technological and business opportunities for the automation of charging services. The proposed secure, resilient, and safety critical architectural framework can be used in modeling, optimizing, and designing a fully autonomous charging station. At present, such locations as office parks, residential buildings, businesses, malls, and parking lots offer free EV charging. This trend of free or relatively inexpensive options for charging EVs may create customer expectations for ubiquitous free charging services. The proposed autonomous charging appears to be the first wide-scale business case for fully autonomous service business, where machines decide when to be serviced, how to adjust the service schedule, and how to pay for that. The business/financial transaction aspect needs to be studied in detail, and secure and scalable solutions need to be developed as its implications will have global impact as it will pave the path to other services that are fully autonomous.

Flexibility and scalability are the major features of the developed analytical platform. In addition to the described flexibility in initialization of vehicle arrival rate and tier distribution, vehicles' energy consumption characteristics can be up- or down-scaled. As fast chargers (450 kWh, 550 kWh, etc.) and correspondingly enhanced batteries become available, one can use this platform to perform various analyses of charging station's operation with state-of-the-art vehicles and chargers. Within such analyses, one can define an optimized number of vehicles that can be serviced with a given number of charging pumps, their distribution, and corresponding sharing conditions. In addition to that, the number of charging pumps can be optimized based on the traffic patterns of a certain area serviced by the analyzed charging station. Besides, the corresponding analysis of energy consumption by a particular charging station under various traffic conditions can be performed through its total load profile defined by a platform. Such load profile can be utilized by ESP for optimization of energy generation and distribution, e.g., through load shifting, reduction of peak-to-valley ratio, etc., benefiting from completely autonomous nature of charging service.

Moreover, if this analytical platform is applied at the multiple sites, e.g., network of charging stations controlled by a single energy service provider, it can be used in a hierarchical way to analyze multiple charging stations within a certain city or state, or the whole country. One the other side, “scaling down” analysis can be performed. For example, feasibility of using single pump for services similar to Airbnb can be analyzed using this platform. Considering flexibility and scalability of the developed analytical platform, its utilization in service with a human-independent ecosystem can be expected to be a major revenue generation application.

In the future work, optimal scheduling procedure and variations in the structures of charging stations can be considered. Each structure will be based on particular design constraints, such as available area and energy capacity of a charging station. Based on these constraints, the total number of pumps available for a charging station as well as the number of designated and sharable pumps at each tier of the station can be defined. In addition to that, the type of AV ownership demographics will also need to be considered in the optimal number of specific featured charging pumps installed in a charging station. Besides, a penalty for charging completion time will be further studied to provide a priority for fast-charging vehicles. Such priority can increase the amount of energy that can be delivered during a given period of time. In addition to that, the embedded security aspect of various integrated layers is also an area where rigorous work would be undertaken.

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