Journal of Cleaner Production 301 (2021) 126877

Contents lists available at ScienceDirect

Journal of Cleaner Production

journal homepage: www.elsevier.com/locate/jclepro

Review

Smart grid architecture model for control, optimization and data analytics of future power networks with more renewable energy

Deepak Kumar Panda [a], Saptarshi Das [a, b, *]

[a] Department of Mathematics, College of Engineering, Mathematics and Physical Sciences, University of Exeter, Penryn Campus, Cornwall, TR10 9FE, United Kingdom
[b] Institute for Data Science and Artificial Intelligence, University of Exeter, Laver Building, North Park Road, Exeter, Devon, EX4 4QE, United Kingdom

ARTICLE INFO

Article history:
Received 26 September 2020
Received in revised form
25 February 2021
Accepted 24 March 2021
Available online 28 March 2021

Handling editor: Prof. Jiri Jaromir Klemeš

Keywords:
Interoperability layers
Smart grid architecture model
SGAM mapping
Smart grid control
Distributed intelligent control
Smart grid cyber-security

ABSTRACT

This paper describes a generic methodology to develop mathematical and computational models of different components of the smart grid architecture model (SGAM). The SGAM inspired integrated mathematical modelling will help develop interoperable complex system simulations for integrating different smart grid components, associated communication models for data exchange and software modules, control, estimation, and data analytics functionalities with the business perspectives. This paper is based on the existing component models inspired by SGAM, which provides a holistic view for integrating the models under operational and security constraints. Achievable results and open research problems for the SGAM mapping have also been discussed in these models supporting the interoperability challenges. The models described in this paper can serve as a guideline to design efficient and robust control strategies for smart grids against uncertain loading, generation, and communication constraints, thus optimizing and improving the whole system's performance. Mathematical and computational models of cyber-physical systems have also been discussed along with their potential challenges. Based on the above concepts, unsolved and open challenges in the smart grid control, optimization and data analytics are highlighted.

Contents

* Corresponding author. Department of Mathematics, College of Engineering, Mathematics and Physical Sciences, University of Exeter, Penryn Campus, Cornwall, TR10 9FE, United Kingdom.
E-mail addresses: dp457@exeter.ac.uk (D.K. Panda), saptarshi.das@ieee.org, s.das3@exeter.ac.uk (S. Das).

https://doi.org/10.1016/j.jclepro.2021.126877
0959-6526/

1. Introduction

There have been several designs and operational standardization attempts for futuristic smart grid technologies. Amongst various philosophies of smart grid design, mainly three standardized models are widely accepted *viz.*

- The NIST (National Institute of Standards and Technology) smart grid conceptual model (Von Dollen, 2009; NIST Framework 2.0, 2010),
- IEEE 2030 standard (IEEE Smart Grid Vision for Computing: 2030 and Beyond, 2013) and IEEE grid vision 2050 (Simard, 2013),
- The smart grid architecture model or SGAM (CEN-CENELEC-ETSI Smart Grid Coordination Group, 2012)(Van Amelsvoort, 2016).

The SGAM is developed by three leading European Standardization Organizations – CEN (European Committee for Standardization), CENELEC (European Committee for Electrotechnical Standardization) and ETSI (European Telecommunication Standards Institute). In response to the European Commission's standardization mandate M/490, these three organizations have developed the SGAM through the SG-CG (smart grid coordination group). The taxonomy for smart grid development from a systems' engineering perspective has been compared using these widely used models in (López et al., 2014) and the usefulness of architectural standards (Albano et al., 2015). Previous studies have shown that the SGAM (CEN-CENELEC-ETSI Smart Grid Coordination Group, 2012) is one of the most prominent ones among these conceptual models for systematic smart grid architecture development due to its clarity of use case management, visualization, and interoperable systems being explicit for modelling, analysis and design (Neureiter et al., 2014).

The SGAM is a cube-like structure, as shown in Fig. 1, consisting of five different interoperability layers (component, communication, information, function, and business). The layers significantly interplay between the information and communication technologies (ICT), energy informatics and business perspectives within the modern and future smart grid technologies (Huang et al., 2017). Each layer is further divided into domains and zones (CEN-CENELEC-ETSI Smart Grid Coordination Group, 2012). The domains span over the full energy conversion chains starting from bulk generation, transmission, distribution, distributed energy resources (DER) and customer premises or loads. The zones are divided according to hierarchical levels of power systems management *viz.* process, field, station, operation, enterprise, and market. Most of the physical energy conversion devices are categorized within the process zone. The field zone includes the protection, control and monitoring devices, whereas the station zone holds the data concentration and functional aggregation modules. In the operation zone, the microgrid energy and distribution management modules are held. The conceptual SGAM model consisting of five interoperability layers, each comprising six domains and five zones, is shown in Fig. 1.

In the SGAM inspired mathematical models, each component (physical hardware, communication channel, data, software, functionality, and constraints) needs to be mapped into the 6×5 matrix, and their inter-connections need to be investigated. The zonal component placement is interpreted based on their respective application. The process zone contains major components that exchange power and cables, loads, sensors and actuators (CEN-CENELEC-ETSI Smart Grid Coordination Group, 2012) while the field zone contains the equipment for control, protection, and monitoring. The data concentrators, functional aggregators, substation automation and supervision modules and devices are placed within the station zone while the energy management and distribution modules of a microgrid are incorporated in the operation zone. This matrix is replicated in the five different layers with a vertical interaction between the functional and business objectives via the data models and communication medium. The SGAM is developed to describe large-scale power systems, substation automation (Faschang et al., 2017) and distribution networks. However, the use of SGAM for integrated complex systems modelling for simulation studies and control design purposes has not been explored, which is the primary motivation of this paper. The models need to be developed by encompassing the inadvertent compromises of the electrical and communication infrastructure.

Due to modern electrical power networks' complexity, we need appropriate tools and processes to manage different layers' architectures from different stakeholders' view. Thus common

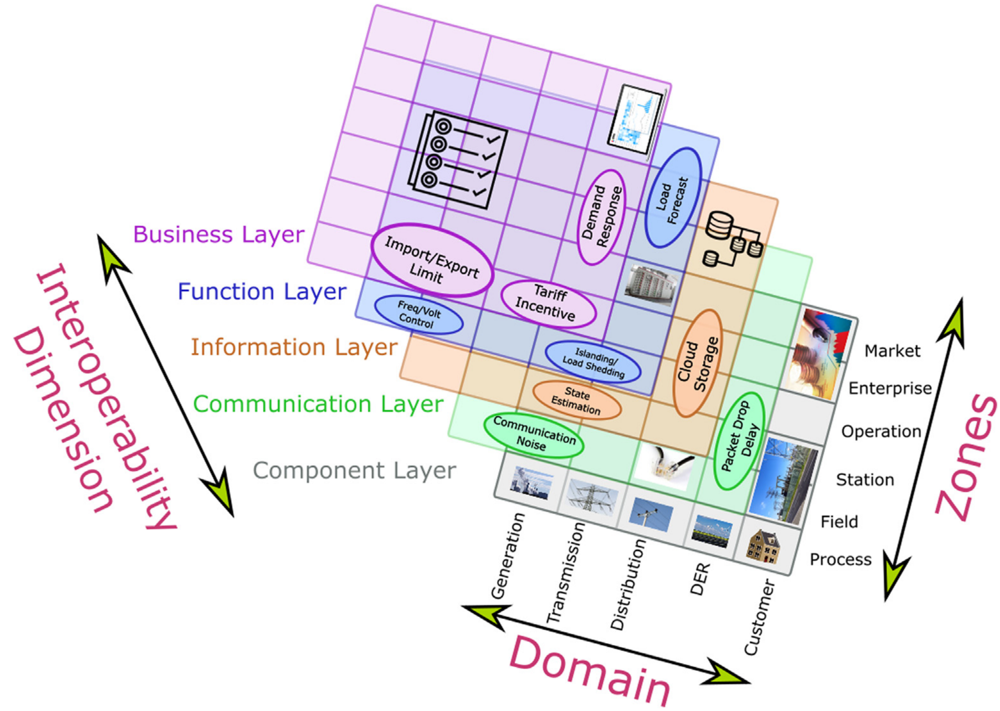

Fig. 1. Five interoperability layers, domains and zones of the SGAM model (CEN-CENELEC-ETSI Smart Grid Coordination Group, 2012).

modelling language and information model has been defined in (Albano et al., 2015), involving different stakeholders. Heterogeneous models, protocols, and interfaces support interoperability and coordination between the smart grid ecosystem components. The importance of SGAM mapping has been explained for use-case management in (Trefke et al., 2013) for technical solutions, development and improvement of the model functionality. Moreover, the taxonomies of the actors involved in the use case management (Andrén et al., 2013), automated engineering methods for platform-specific deployment (Santodomingo et al., 2014), also helps in gaining insight into the potential security issues (Trefke et al., 2013). Architecture visualization of the common information exchange based on the use case management model has been discussed in (Neureiter et al., 2014), (Santodomingo et al., 2016) where a tool-chain is structured based on international standards. The American NIST smart grid architectural framework (as shown in Fig. 2) is mapped into the European SGAM (Uslar et al., 2014) structure to obtain secure architecture development, facilitating the design of adaptive adequate ICT architecture based on the specific enterprise needs (Trefke et al., 2012). The NIST framework's priority areas involve demand response and consumer energy efficiency, wide-area situational awareness, distributed energy resources, energy storage, electric transportation, network communications, advanced metering infrastructure (AMI), distribution grid management, and cybersecurity. Ontology for defining vocabulary and taxonomy to capture the smart grid's business and engineering aspects is defined in (López et al., 2015) along with the algorithm (Nieβe, Trö;schel and Sonnenschein, 2014) for the ICT.

IEC 61850 (Mackiewicz, 2006) and IEC 61499 (Vyatkin, 2011) are interoperability standards between the functional and information layers for smart grid protection and control applications where former is used to model the distributed automation systems and the latter models distributed industrial automation systems. Semi-formal boilerplate model has been utilized to tackle the complexity of developing smart grid automation software in (Yang et al., 2019), which is presented in the form of an ontological model fulfilling the smart grid functional requirements by translating the IEC61499 standard control codes for protection and control system design into restricted natural language (RNL). The ontological representation provides a common ground for a set of notations used for models used in different layers. Multimodel co-simulation platform has been described in (Barbierato et al., 2020) based on different SGAM layers representing general-purpose services in smart grids. The co-simulation platform will help validate different smart grid policies in the form of algorithms thus facilitating interoperability between different virtual and physical devices (like circuit breakers, isolators, smart meters, etc.) via geographically distributed Internet of Things (IoT) or communication paradigms while considering the fast transient phenomenon as well as communication latency. The solution is compliant with IEC 61850 and ISO 17800 standards, which deals with the interoperability of intelligent electronic devices (IEDs) and control centres. The testbed operations were analysed with standard fault detection, islanding, and restoration (FDIR) schemes with centralized and decentralized strategies. Reference architecture model edge computing (RAMEC) has been described in (Willner and Gowtham, 2020) to fulfil the gap in the industrial edge computing in the SGAM paradigm where 210 distinct interdependent fields were identified as the potential introduction of substrate layer for data trustworthiness. The SGAM platform for testing new use cases have been described in (Estebsari et al., 2019), which focuses on wide-area monitoring of distribution systems under the increased PV penetration. The analysis was performed considering the unavailability of the smart meter data. Safety and security of critical infrastructures, without the aid of historical data, require human intervention which can be addressed using conflicting incentives risk analysis (CIRA) where participating stakeholders define the risks. Hence the inclusion of the human element in the SGAM model was discussed in (Szekeres and Snekkenes, 2020), thus proposing the SGAM-H model. The human layer is modelled with an intra-organizational risk factor with the CEO managing the identified risks amongst different stakeholders. Framework for incorporating e-mobility systems

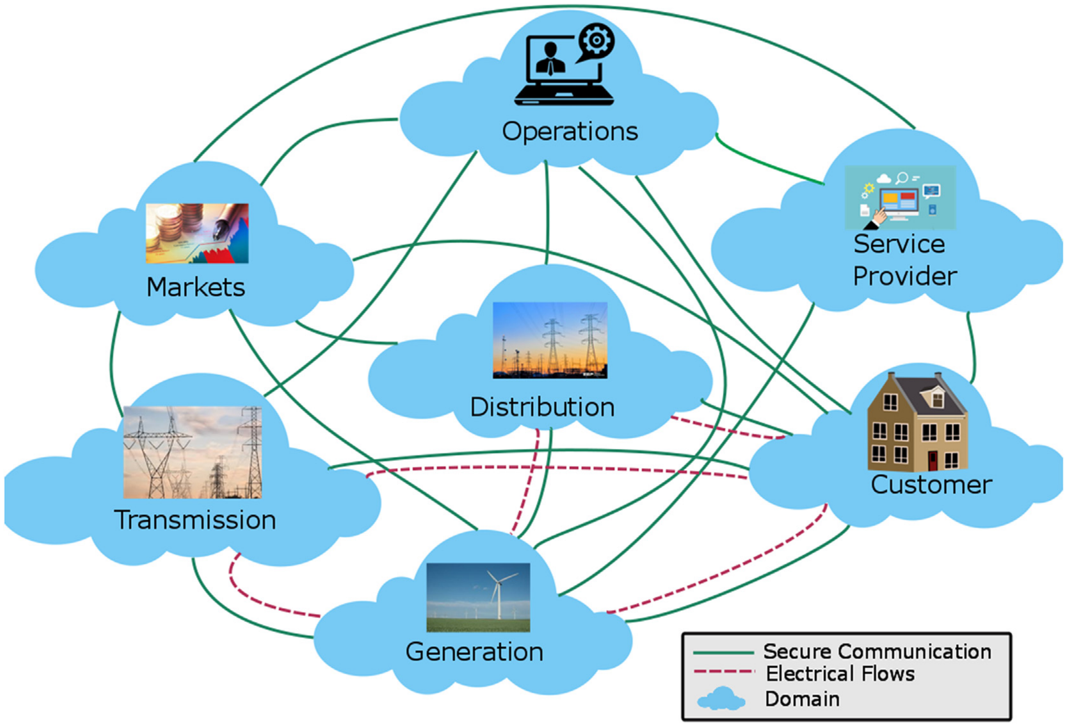

Fig. 2. Smart grid conceptual model NIST (Von Dollen, 2009; NIST Framework 2.0, 2010).

architecture (EMSA) in SGAM has been discussed in (Kirpes et al., 2019) where the mapping has been considered incorporating functional reference architecture, harmonized model, and data and communication standards.

Within the SGAM framework, various aspects of the smart grid have been described e.g. peer to peer energy trading (Zhang et al., 2016), integration of distributed energy resources (McGranaghan et al., 2016), distributed control (Guillo-sansano et al., 2016), laboratory infrastructure (Syed et al., 2017), e-mobility for electric cars (Schuh et al., 2013), power quality (Gustavsson et al., 2013), security management (Kammerstetter et al., 2014), distributed automation for distribution networks (Angioni et al., 2017), advanced metering infrastructure (Dänekas and González, 2013), railway energy management (Khayyam et al., 2016), virtual power plant (Etherden et al., 2016), substation automation (Leonardi et al., 2014), wireless communication (López et al., 2014), software-defined networking (Molina et al., 2015) etc. However, this paper focuses on establishing the mapping of the components to conduct simulation studies for control, optimization, and data analytics to highlight the concept of SGAM model on a broader context. Integration of these components can be obtained to increase the capacity, reliability and efficiency of the electrical grid with cyber-physical systems (Ma et al., 2017). This fusion opens up many vulnerabilities, hence making cyber-security of future smart grids a challenging task. Therefore, it is important to use mathematical and statistical models for cyber-attack analysis, addressing security and privacy concerns, as shown in (Srivastava et al., 2013). On the real smart grids, cyber-attacks may have different random characteristics. Hence this paper has also highlighted their existing models which can affect the communication and information layer of the SGAM. Moreover, the study will focus on the identification methods of random cyber-attacks on smart grids using various data analytics and machine learning algorithms, hence improving future smart grid technologies' resilience. The main highlight of the paper is given as follows:

- Mapping the existing works in the field of smart grid modelling within the layers, zones and domains of the SGAM and relating the interoperability between different layers.
- Identifying the cyber-security challenges and vulnerable areas in the existing works which influences the SGAM layers.
- Discussing the potential research directions to realize the smart grid vision for 2050.

The paper is organized into four sections. Section 2 focuses on mathematical models where SGAM components are mapped into a 2D matrix of domains and zones. Section 3 focuses on the modelling of cyber-attacks and its identification techniques. Section 4 discusses the future research direction of applying the integrated mathematical model of the SGAM, followed by the conclusion in Section 5.

2. Mapping of mathematical models in the SGAM architecture

The paper first reviews the existing models and architectures for various SGAM components. Hence the following principles have been adopted while mapping these models in the 2D matrix like architecture of SGAM:

- Identifying the components in the 2D matrix of domains and zones,
- Understanding the functionality of each component for one or more purposes and
- Understanding the details of the communication and data exchange between components.

This paper presents a pictorial overview of the mathematical models of various components' in the smart grid landscape in Fig. 1. Functional clusters are grouped to identify topologically similar communities. The domains are divided based on the management hierarchy of different components. The data concentrator, controllers, computers for data storage, holding control and optimization routines, set-point generators and market inputs from the actors (Hussain, Gustavsson, Saleem and Nordströ;m, 2012), are expected to be gradually placed in higher zones.

Each SGAM layer is divided as a 6×5 matrix (1) and the items in each interoperability layer using initials, e.g. layer $l = \{\mathrm{Comp}, \mathrm{Comm}, \mathrm{I}, \mathrm{F}, \mathrm{B}\}$ which are collected together to construct each element of the matrix as:

$$SGAM_{l=\{\mathrm{Comp,Comm,I,F,B}\}} = \{M_{ij}\},\quad i = \{\mathrm{M,E,O,S,F,P}\},\ j = \{\mathrm{G,T,D,DER,C}\} \tag{1}$$

Here, M_{ij} denotes each element in the SGAM which may contain multiple physical components. Elements of each SGAM layer can be described as (2) where i span across the 6 zones and j span across 5 domains:

$$SGAM_{l=\{Comp,Comm,I,F,B\}} = \begin{bmatrix} M_{11} & M_{12} & M_{13} & M_{14} & M_{15} \\ M_{21} & M_{22} & M_{23} & M_{24} & M_{25} \\ M_{31} & M_{32} & M_{33} & M_{34} & M_{35} \\ M_{41} & M_{42} & M_{43} & M_{44} & M_{45} \\ M_{51} & M_{52} & M_{53} & M_{54} & M_{55} \\ M_{61} & M_{62} & M_{63} & M_{64} & M_{65} \end{bmatrix} \tag{2}$$

For each layer (l), the elements are collated in the appendix section. The equality of some of the elements signify similar operational characteristics across different SGAM components. This mapping technique helps understand each mathematical model's importance in (1) stacking the layers in (2) to describe a specific smart grid application by constructing a 3D cube-like architecture. The elements of each layer are then identified and mapped on the SGAM planes. Some of the elements in (1) may have empty cells, unless and otherwise specified.

2.1. SGAM component layer

An electrical power system is divided into three key domains: generation, transmission, and distribution. The conventional power generation scheme consists of a synchronous generator, where the 3-phase electrical energy is generated from the prime movers' input mechanical energy (steam, gas, hydro turbines). The output voltage is stepped up and down in the transmission and distribution substations, respectively, as shown in Fig. 3. The conventional distribution systems are aided by DER like solar, wind, marine etc. interfaced with power electronic devices to cater to the loading requirements. The customer premises mainly consist of loads which are modelled based on their active and reactive power requirements.

Thermal power plant model has been described in (Prasad et al., 1998; Prasad et al., 2000) using a local model network (LMN) where its load cycling operation models its nonlinearities. The derived model showed excellent control performance on various operating conditions. However, the thermal power plant's block performance improves in conjunction with the energy storage elements described in (Powell and Edgar, 2012; Montes et al., 2009). The model explains the integration of parabolic trough as an energy storage unit that improves the power plant's overall performance by steadying the power output under varying solar conditions to reduce the supplementary fuel. The 3-phase electric power is produced from the synchronous generator coupled to the turbine, whose state-space model is given in (Kundur et al., 1994), along with the exciter.

The generated power is transmitted to consumers using transmission lines, as shown in Fig. 3. They are generally modelled using classical two-port network theory using the π-model and T-model for short and medium transmission lines respectively as given in (Kundur et al., 1994). The sinusoidal travelling wave model is used for the representing long transmission lines that relaxes the lumped parameter assumption. However, the power networks connecting various generators and loads via the transmission lines are generally modelled using the admittance and impedance matrix. This modelling technique is useful to conduct power flow (Stagg and El-Abiad, 1968; Tinney and Hart, 1967) and short circuit analyses (Zhang et al. (1995), respectively. The transformer's role is crucial since it facilitates power transmission at high voltage, as shown in Fig. 3, thus improving the overall efficiency by minimizing the losses. The transformer is modelled in the transmission power

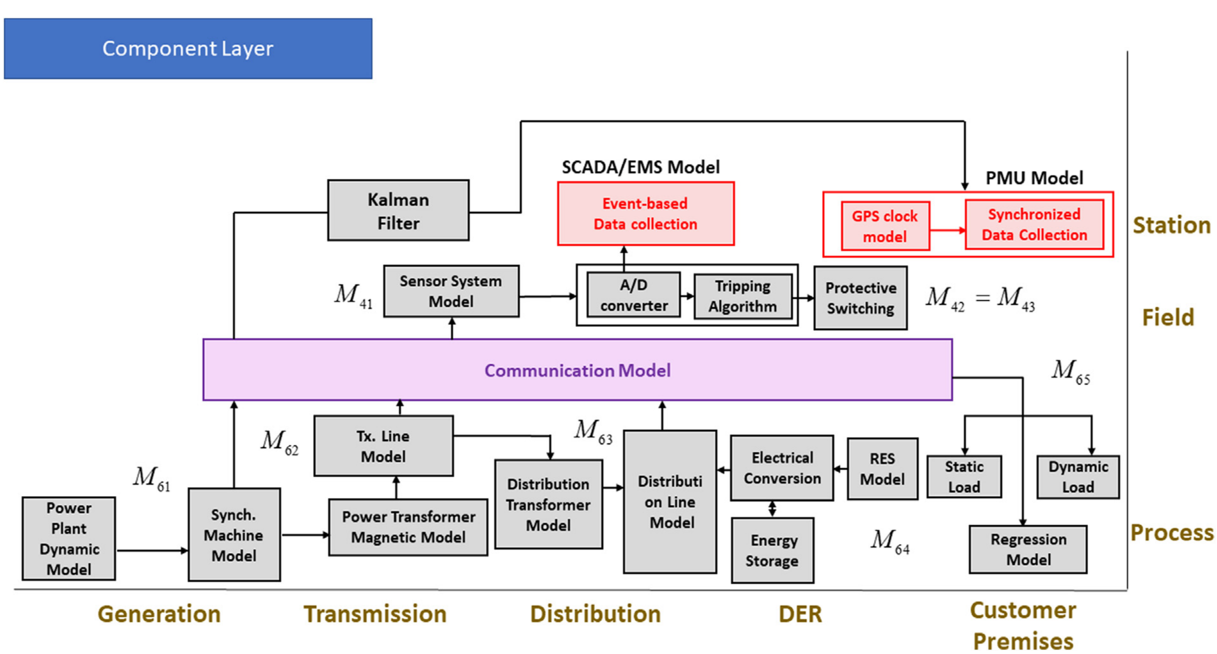

Fig. 3. Mapping on the SGAM component layer (grey - component layer models, purple - communication layer, red - information layer).

network by modifying the Y-bus matrix parameters, incorporating its magnetic parameters and voltage transformation ratio (Kundur et al., 1994).

The transmitted power is provided to consumers using distribution systems. They are modelled as an agglomeration of several microgrids consisting of several AC and DC loads described in (Olivares et al., 2014). The microgrids mainly incorporate renewable energy sources (RES) from the local consumers and small-scale business units. Their electrical integration with the grid is shown in Fig. 3. Due to the technical, economic, and environmental benefits, solar power, photovoltaic (PV) systems have become a popular investment among different DG systems. PV array is modelled based on its current and voltage characteristics (Hussein et al., 1995). It is integrated with the distribution system model (Yazdani and Dash, 2009) and other hybrid renewable energy and storage systems (Lee and Wang, 2008) using power electronic converters whose interface with the grid is discussed in (Carrasco et al., 2006) along with modelling and control (Forsyth and Mollov, 1998) and small signal stability analysis (Coelho et al., 2002).

A wavelet variability model captures the solar PV plant output for a single irradiance point sensor time-series using spatio-temporal correlations (Lave et al., 2012). Another DER source is wind power, where the doubly fed induction generator (DFIG) is used along with the wind turbine system. This interface provides ease of control, ensuring high energy efficiency. Mathematical model of the DFIG and wind turbine is discussed in (Slootweg et al., 2003), (Abdin and Xu, 2000), (Lei et al., 2006) along with the static var compensator (SVC) and transmission line model. In (Slootweg et al., 2003) direct drive synchronous generator is described along with back to back voltage source converter. The wind turbine is modelled using aerodynamic principles and pitch control techniques, where it is described along with its electrical interface.

There has been a considerable increase in the activities in the offshore renewable energy sector. Cost-effective ways have been developed to harness maximum power from its high potential. Physical modelling of the wave energy converter is described along with statistical properties of the sea waves in (Wu et al., 2008; Penalba et al., 2017). Its performance is studied under various operating conditions, while designing wave energy converters in (Li et al., 2012). The electrical interface of the wave energy converter has been modelled in (Wu et al., 2008). Its impact on the large scale power systems has been studied in (Das and Pal, 2006).

The problem with the RES based power system, as described above, is the dependency on the weather and environmental conditions. Hence, it is essential to characterize the uncertain conditions resulting in a more efficient and robust power system. Statistical tools like Bayesian networks (BN) are used which provides probabilistic models for the uncertain components of the power system (Borunda et al., 2016). The theory is also applicable to solar, thermal, photovoltaic, geothermal, hydroelectric, and biomass energy resources to address the issues of forecasting, fault diagnosis, maintenance, operation planning, sizing, and risk management.

The energy storage technology is the key to the future development of the RES as they help mitigate the associated uncertainty. As discussed in (Gyuk et al., 2005), battery storage is the most commonly used storage device for power system applications. Various battery models along with its role in power system stability is discussed in (Lu et al., 1995), and their impact on the power system stability is also compared. The models of battery are used in conjunction with the solar PV (Copetti et al., 1993), wind energy system (Teleke et al., 2009) to address the functionalities like frequency control (Mercier et al., 2009), (Kottick et al., 1993), renewable energy dispatch and power smoothing control (Teleke et al., 2009), (Li et al., 2013).

Due to advancement in various other storage technologies, e.g. flywheels, fuel cells, and ultracapacitors have become a promising alternative to battery storage systems. As reviewed in (Bolund et al., 2007), flywheel operations help ride through application in a facility microgrid (Arghandeh et al., 2012). The flywheel can provide peak power for a short period, and its fast response is used to balance grid frequency oscillations and correct the voltage sag (Samineni et al., 2006). Moreover, flywheel energy storage system (FESS) in (Arghandeh et al., 2012) provides highly reliable ride through for critical loads during grid disturbances. The ultracapacitors (UC) are used with the electrical system to improve their performance and reliability owing to high power density and charging/discharging capacity. The UC model is described in (Shi and Crow, 2008) using various resistance-capacitance (RC) branch circuit models while considering the electrolyte parameters. The UC provides extra power to fuel cell (FC) plant during peak and transient periods as given in (Uzunoglu and Alam, 2006). The UC-FC energy system described above is modelled based on the residential power demands where the control algorithms govern their power flow. The dynamic model of a wind and fuel cell energy system is simulated in (Khan and Iqbal, 2005), consisting of a 400W wind turbine and proton exchange membrane fuel cell (PEMFC), ultracapacitor, and electrolyte and power converter. Fuel cell stack helps in damping out the wind power output fluctuation. The dynamics of components in the isolated system has been simulated, including the temperature and capacitance variations.

The loads in power flow analysis in (Tinney and Hart, 1967) are generally represented by constant active (P) and reactive (Q) power. The load dynamics mainly affects the grid voltage and frequency (Kundur et al., 1994), (Milano, 2005), (Hirsch, 1994). The load model can also be built using statistical methods based on regression models and forecasting techniques (Haida and Muto, 1994). It is therefore essential to study the stability of power systems and smart grids under several anomalous conditions. The faulty conditions are simulated with the shunt impedances, and their impacts have been studied using clearance times in (Milano, 2005). The circuit breaker in the field level is used to clear the faults in power systems. Reliability models have been developed for the circuit breaker in (Lindquist et al., 2008). The data from several failure modes of the equipment can be utilized to optimize their maintenance frequency. The circuit breakers operate on the relays' decision logic, which in turn utilizes the field measurements and specified operating time. The numerical relays are preferred over the analog hard-wired relays due to the compact nature, reliability, flexibility, and ease of communication. The hardware and software operations of the DBZ-500 relay are modelled in (Kezunovic and Guo, 2000), and the simulation characteristics were studied. The hardware part consists of the isolation transformer, anti-aliasing filter and analog-to-digital (A-D) converter, as shown in Fig. 3, which converts the operational data for feeding into software systems.

The overview of the computational tools for modelling, analysis and simulation of the component layer is described in (Mahmud et al., 2020). Moreover, computational tools are also mapped in the component layer of the SGAM model. The power generation simulation schemes involve thermal power station, wind power, hydropower, photovoltaics, geothermal, biomass and fuel cell. In addition to that, it also includes a review of computational tools which facilitates modelling, simulation, and data analysis of the following components:

- Transmission and distribution systems,
- Transformers and substations,
- Substation operations,

- Overhead, underground and grounding methods,
- Different grounding technologies,
- Power flow and short circuit of power networks,
- Integration of distributed energy resources in the smart grid,
- Power quality and stability of integrated power systems,
- Power system protection schemes.

Power systems models and their functionalities, as described above, are used to study the overall functional behaviours of the smart grid and meet the regulatory policies. Hence, it is essential to provide an interface between these models and upper hierarchical levels using ICT, described in the communication and information layers, in the next sub-sections.

2.2. SGAM communication layer

The communication layer's primary purpose is to interoperate between manual control and multiple automatic controllers, sensors, and actuators in the physical layer. Scalable, robust, and secure communication infrastructure is vital for the design and secure operation of smart grids. Several industrial trials and requirements of communication paradigms are described in (Yan et al., 2013). Monitoring, sensing, communication, and control standards of distribution systems need to be robust enough to meet the latency and the bandwidth challenges for communication systems. The timely propagation of sensing and control messages keep the functional characteristics of the grid intact.

Several major communication technologies have been described in (Yan et al., 2013) which include IEEE specified Zigbee, WiMAX and wireless LAN technologies, GSM 3G/4G cellular and DASH7. These communication technologies are applied to smart grid domains like home area automation, substation automation, automated metering infrastructure, and vehicle to grid communication. The primary focus of smart grid communication is currently on the consumer domain, especially developing solutions for plug-in electric vehicles (PHEV). The issue of standardization and interoperability of the communication standards is a fundamental research challenge.

The most common standard of communication in power systems and smart grids is the power line communication (PLC) as described in (Galli et al., 2011), which is commonly utilized in high, medium and low voltage power networks. The deterministic and stochastic models based on the communication standards, are integrated with the power networks, as shown in Fig. 4. The topology of the power grids is described along with the PLC models such that the network dynamics, along with the data traffic and fading channel models, can be studied. The model described in (Katayama et al., 2006), (Meng et al., 2005) explains the non-white features of the modelled noise in the channel along with time-varying parameters in narrowband frequency line. The digital modulation schemes' performance is compared in the communication systems, as shown in Fig. 4. The additive noise and channel model has been characterized by the power flow at 50 Hz or 60 Hz grid frequency as given in (Nassar et al., 2012). It is shown that due to the presence of the transformers, the communication lines undergo attenuation, frequency selectivity plus other nonlinear impairments. The solution has been provided in the context of single and multi-carrier narrowband PLC standards. It enables two-way communication between customer premises and control centres. The wireless sensor network's reliable operation is very challenging in the Industry 4.0 paradigm, used in the smart grid context. It is mainly due to the presence of noise and interference in the network. A robust communication network is required to successfully operate wireless sensor networks (WSNs) in smart grids. A dynamic clustering based optimized protocol is explored in (Faheem and Gungor, 2018) where it improves the system's reliability by reducing the excessive packet retransmitted in the smart grid communication networks.

In order to mitigate the uncertainty and noise present in networked systems, the control strategy should be devised to ensure optimal system performance under stable conditions. The control methodologies to handle the effect of delays and ensuring the stability of the networked system has been discussed in (Tipsuwan and Chow, 2003) and the application of NCS in various similar domains has been discussed in (Gupta and Chow, 2009). The stability analysis of the networked control system were carried out with random effects in communication (Liu et al., 2006) and uncertain delays (Cloosterman et al., 2009). The effect of communication parameters in system performance degradation and destabilization are described in Fig. 4. Various state estimation techniques have been studied in (Hespanha et al., 2007) and their system behaviour analysis between various transmission times (Montestruque and Antsaklis, 2004). System stability studies are conducted using linear matrix inequalities (LMIs) (Cloosterman et al., 2009), at variable time intervals (Montestruque and Antsaklis, 2004). The threshold packet drop rate for maintaining system stability has been discussed in (Azimi-Sadjadi, 2003). Hence considering the system stability and performance studies, (Liu et al., 2006; Tipsuwan and Chow, 2003), bandwidth allocation and scheduling, network security and fault tolerance (Gupta and Chow, 2009), various control strategies were developed. System stability studies and control strategies can also be developed using an emulation of real-time communication standards (Walsh et al., 2002) and server-client intranet servers (Liu et al., 2006) where the former takes into account the multiple adopting protocols in case of a failed transmitted data.

In order to test the control algorithms with the communication parameters for smart grids, it is essential to validate them on a co-simulation platform of power and communication networks as described in (Roche et al., 2012). Control algorithms on state-space models are tested in MATLAB platform using TrueTime (Henriksson et al., 2003; Cervin et al., 2003) and Jitterbug (Cervin et al, 2003, 2006). The comparison of these toolboxes suggests that the latter provides a better quantitative result of control loop performance while the former can demonstrate the transient behaviour of systems by replicating the CPU kernels and network performance. The simulation aspects of both the platforms have been combined where the former is used to model sampling delay distributions and input-output latencies, while the latter is used to evaluate the control performance with the quadratic performance criterion. In (Roche et al., 2012), the power system is simulated in a DIGSILENT environment where it is interfaced with the artificial intelligence algorithms through a Java agent-based environment (JADE) and communication simulator OMNet++. The interfaced testbed is used to study the voltage regulation problem in a distribution system to realize the coupled power and communication networks. The state of the art network simulator NS3 is used along with the power simulator Power World in (Tariq et al., 2014) to simulate the effect of link delays, different packet drop rates and application update period in demand response scenarios as shown in Fig. 4. Since the NS3 simulates variable layer of a computing node by supporting an extensible model of the application layer, it is used to study the effect of communication systems in complex smart grid scenarios. The communication layer developed in OMNet++ is interfaced with the popular power systems simulator in MATLAB (Mets et al., 2011). The impact of distributed generation on the grid has been observed by their respective load and the voltage profiles. The advantages of various simulation platforms are presented in (Li et al., 2014) using decision tree flowchart. The challenges of integrating communication simulators with the power simulator are described since the former is event-driven while the latter is time driven.

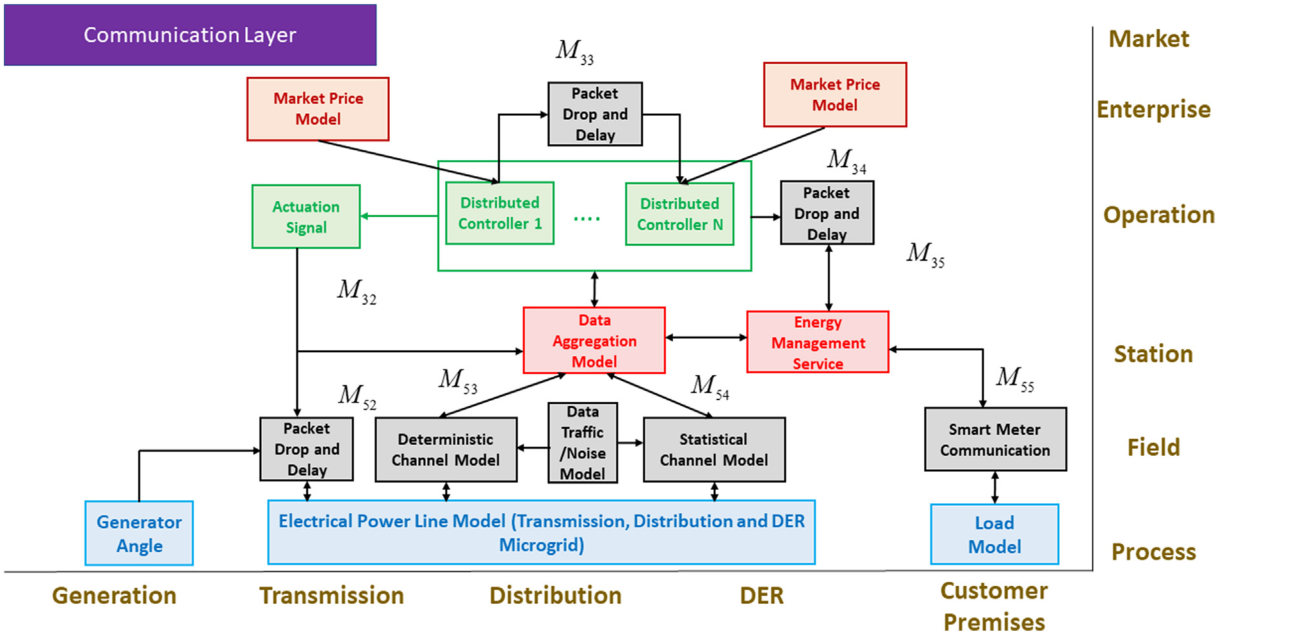

Fig. 4. Mapping on the SGAM communication layer (grey - communication layer, blue - component layer, red - information layer, green - functional layer, brown - business layer).

The interconnection between power and the cyber network is studied in (Korkali et al., 2017), which shows that increased coupling between the network can make the system more vulnerable to failures. Hence, to study cascaded networks' dynamics, a simple topological model's robustness is compared with the percolation model. The power system data has to be managed after transmission from the sensor networks in the power grid via communication channels as modelled in this layer. The data is managed in the information layer, and various techniques are explained in the following sub-section.

2.3. SGAM information layer

The information layer facilitates data exchange and storage for smart grid protection and control applications. Revolutionary ICT technologies are required to achieve the smart grid's robustness and reliability under a highly dynamic network of consumers and producers. The standards - IEC 61850 and IEC 61499 provide automation architecture that supports multi-agent intelligence and distributed automation simulation (Zhabelova and Vyatkin, 2012). The SimPowerSystems in Matlab is used for validating custom-designed user datagram protocol (UDP) socket. For achieving the optimal efficiency of the multi-agent network, it is essential to have robust operability between them under various operational network topologies (Sabater and Sierra, 2002; Pujol et al., 2002). They are also used to represent power-producing and consuming agents. The balance between supply and demand is maintained using market algorithms validated using PowerMatcher software in (Hommelberg et al., 2007).

The information exchange in power systems should not be accessed through local gateways as it risks end-user's privacy and security. End to end encryption preserves the privacy of the data. However, it increases the data size causing unacceptable communication overhead. Hence an efficient privacy-preserving aggregation scheme is proposed in (Lu et al., 2012) for secure smart grid communications and in (Erkin et al., 2013) for smart meter data by preserving data integrity (Li and Luo, 2012) and anonymization (Efthymiou and Kalogridis, 2010) which not only improves the communication operations, but also ensures the consumer privacy (Mármol et al., 2012). Security analysis for the above aggregation scheme showed efficient performance. A different topology is described in (Li et al., 2010) where data aggregation is performed at multiple levels based on the hierarchy and frequency. This topology is helpful for load allocation and power generation administration. However, in (Rottondi et al., 2013), the security architecture is defined using multiple gateways at customer premises, providing communication and cryptographic abilities amongst themselves and external entities thus facilitating privacy preservation. Homomorphic encryption is used for smart meters (Garcia and Jacobs, 2010; Mármol et al., 2012; Li et al., 2010), in demand response schemes (Lu et al., 2012), thus securing the users' session using adaptive key evolution. The overall efficiency is achieved using a trade-off between communication and security level. The threshold of secret shares for similar groups resists a differential attack from the data aggregators and the control centre (Guan and Si, 2017). The users' identity is masked using the group serial number. Hash table is used to find the malfunctioned smart meters, thus achieving the objective of fault tolerance. Energy disaggregation is an active field of research, where the appliance energy consumption data from the smart meter is used in the algorithm (Kelly and Knottenbelt, 2015). The "last-meter smart grid" helps the customers exchange their power consumption information with the energy providers and distributors at a much granular level whose architectural framework is defined using heterogeneous communication protocol (Spanò et al., 2015). Hence secure data access is provided by mapping each sensor and actuator to a more common abstract layer.

The data is abundantly available due to widespread deployment of multiple sensor networks and information exchange in smart grids. Hence, data compression is essential for effective management, which has to meet low memory and overhead requirements. Various compression techniques like wavelet transform, singular value decomposition (SVD), wavelet packet transform (WPT) and Lempel-Ziv-Welch (LZW) are discussed and compared in (Wen et al., 2018). However, the embedded zero wavelet transform (EZWT) provides better results than standard wavelet transform techniques with efficient utilization of the data storage system. Moreover, it also removes noise with minimal signal distortion and mitigates the communication system's burden (Khan et al., 2015). Predictive modelling can improve the compression performance with the fast trend visualization and analytics of the stored data (Kraus et al., 2012). Data compression has been executed by extracting features from the base state and load event detection and clustering from the Irish smart meter data (Tong et al., 2016).

Another strategy to tackle the abundance of ever-increasing data is cloud computing usage with the rapid progression of information technology (IT). Cloud computing is one of the supportive technologies for the next level smart grid that can potentially provide a smarter, automated, and distributed network storage of the data collected from the smart meters and the sensors deployed in the smart grid networks. The application of cloud computing servers in the high-performance computing simulations of power systems is discussed in (Fang et al., 2016) for power flow simulation and optimal dispatching, as shown in Fig. 5. It can also be used to segment the data coming from the smart meters. They are also used to find hidden patterns of energy consumption based on statistical features of the data (Räsänen and Kolehmainen, 2009), working patterns of the customers (Benitez et al., 2014), seasonal patterns (Räsänen et al., 2010) and the nature of the observed peaks (Kwac et al., 2014). These patterns help the utility sectors to formulate different tariffs based on various consumption patterns. The load consumption can also be forecasted using smart meter and weather data given in (Papalexopoulos and Hesterberg, 1990), (Djukanovic et al., 1993) which aids various utilities. The ancillary services from the electric vehicles are regulated using real-time analytics of the people's mobility patterns from the cloud server, as shown in (Mureddu et al., 2016) along with load and weather patterns as shown in Fig. 5. The smart grid data mining and analytics depend upon the quality of information stored in the servers where the issues are highlighted in (Chen et al., 2017), which includes noisy, incomplete and missing data and outliers. It is shown that advanced data mining techniques provides satisfactory performance in the detection and elimination of outlier data, as shown in Fig. 5.

Other than the cloud server's real-time analytics in smart grids, it can also help bridge the paradigm between energy production, transportation and consumption along the whole value chain (Bui et al., 2012). IoT is the integration, collaboration, and communication of real-world objects in order to perform a task efficiently. Thus, IoT interoperable standards are used for distributed nodes to improve the local monitoring and control of energy usage in smart grids. The concept of Internet of Energy (IoE) is used for the coordination of various energy storage systems, renewable energy source interface to the grid, demand-side management, electric vehicles management in smart grid (Moness and Moustafa, 2015; Jaradat et al., 2015), integration of heterogeneous devices in home and building energy management systems (Karnouskos, 2010) and flexible energy sharing in residential energy distribution system (Huang et al., 2010). The messaging protocol of a universal IoT gateway has been developed in (Viswanath et al., 2016) to address the critical factors for efficient energy management and improve user's lifestyle. The protocol is validated on a testbed consisting of sensors, actuators, smart-plugs and smart-meters. Contingency management of the power system has been described in (Ciavarella et al., 2016) using an IoT paradigm by curtailing the respective loads using linearized network equation.

The power system operating conditions are monitored using phasor measurement units (PMUs). It plays an essential role in the collection of high-resolution data, synchronized with the GPS clock. These measurements are used for stability analysis and monitoring, protection, state estimation, fault location identification and loads with fast dynamics (Sexauer et al., 2013), thus improving the dynamic model's integrity (Huang et al., 2013), (Zhou, Meng, Huang and Welch, 2014b) and removal of bad data (Chen and Abur, 2006). Power system state estimation plays an essential role in planning and optimal power flow studies for distribution systems, as shown in Fig. 5 and described in (Zhou et al., 2014b), (Ahmad et al., 2017). The statistical measures used in the estimation algorithms to evaluate the robustness against measurement and process noise, sensitivity against sampling intervals and its convergence characteristics have been discussed. The deployment of PMUs for preserving the system observability with optimal investment has been analysed in (Yang et al., 2013; Abbasy and Ismail, 2009). Clustering algorithms on the PMU measurements have been used to find the disturbance events (Edwards et al., 2012; Dahal et al., 2013) and dynamic signature (Guo and Milanovic, 2015) in

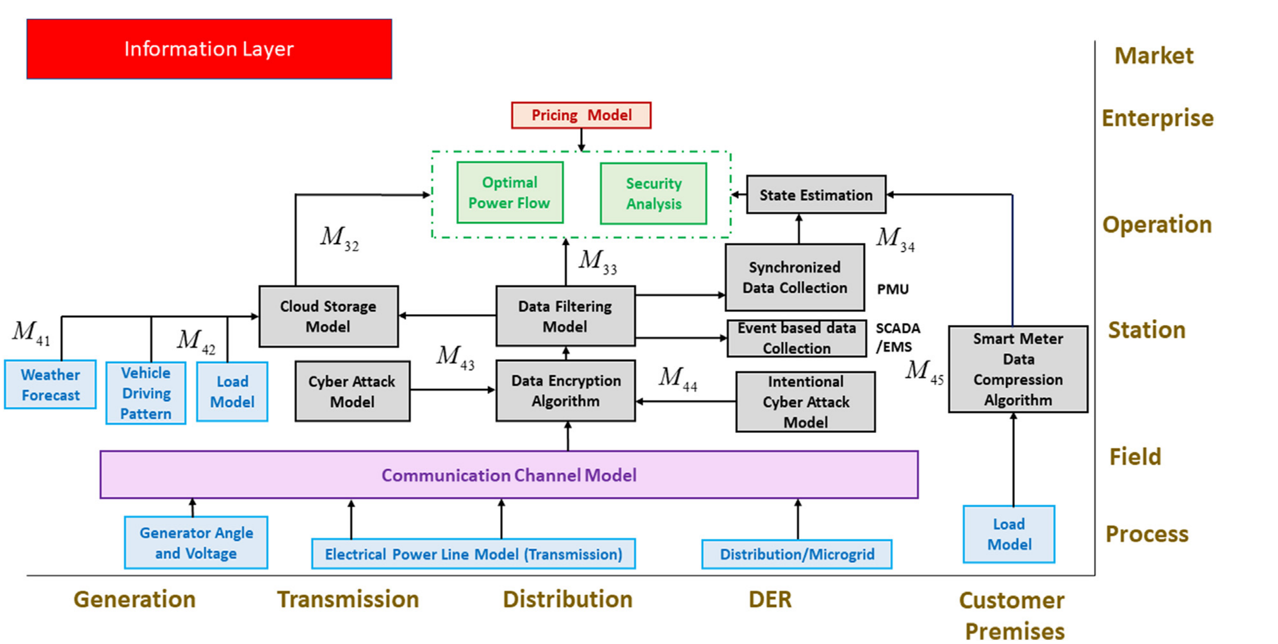

Fig. 5. Mapping on the SGAM information layer (grey - information layer, blue - component layer, purple - communication layer, green - functional layer, brown - business layer).

the power system using big data analytics framework as provided in (Edwards et al., 2012).

Information access schemes between remote assets and controllers are described in (le Fevre Kristensen, Olsen, Rasmussen and Schwefel, 2018), which are activated when the voltage measurements cross a certain threshold. The mathematical model for the non-ideal information access schemes: information age and mismatched probability have been defined in (le Fevre Kristensen et al., 2018) and validated by numerical simulation results. Markov model is used to capture the behaviour of the power grid voltage for the mismatched probability distributions. The data collected from various parts of the smart grid-like power networks and customer premises are used for various functional schemes, to operate the grid athigh efficiency, as described in the following section.

2.4. SGAM functional layer

The functional layer platform used in SGAM consists of various control functions, incorporated in the local power controller (LPC) or distributed systems (Roscoe et al., 2011). The LPC provides vital functions to the management of local generation and load assets and has various features, including:

- Frequency estimation (Clarke - FLL hybrid) (Roscoe et al., 2009)
- Frequency - active power (*f*-*P*) droop control (Bevrani and Shokoohi, 2013)
- Voltage - reactive power (*V*-*Q*) droop control (Vasquez et al., 2009)
- Automatic islanding for low-frequency operation (Roscoe et al., 2011)
- Dynamic load shedding based on load priority (Xu et al., 2011).

The frequency estimation algorithm from the three-phase AC measurement of voltage and current has been presented in (Roscoe et al., 2009). It works reliably even in the presence of phase unbalance, noise contamination and harmonics. Active power control is an essential function in power systems where any mismatch between the power generation and consumption can lead to frequency imbalance as per the swing equation model in (Kundur et al., 1994) as shown in Fig. 6. Hence several strategies have been developed for power systems using PI controllers (Kothari, Nagrath and others, 2011), adaptive PI controllers (Talaq and Al-Basri, 1999; Pan and Liaw, 1989), H_∞ and LMI formulation for robustness against parameteric uncertainty along with optimal tuning of PI controller parameters (Rerkpreedapong et al., 2003), robust sliding mode control (Yuan et al., 2015) and various other multi-level and hierarchical control strategies incorporating nonlinear power system models, battery energy storage, wind turbine and PV dynamic models, as discussed in the component layer section (Aditya and Das, 1999; Kumar, Kothari and others, 2005). Artificial intelligence-based control for frequency regulation, based on active power, has been utilized using neural networks (Beaufays et al., 1994), (Demiroren et al., 2001) and evolutionary and swarm optimization techniques (Guha et al., 2016; Ali and Abd-Elazim, 2011; Panda et al., 2020). The analysis of the load frequency control technique with the incorporation of renewable energy has been tested and analysed under various stochastic profiles in (Panda et al., 2020) with communication delays and packet drop scenarios. The active power regulation using current controller for distributed power generation system (Timbus et al., 2009), for distributed generation inverters under unbalanced grid faults (Wang et al., 2010) and for voltage source converter (VSC) high voltage DC (HVDC) were studied while analysing system stability, performance and robustness (Wang et al., 2014).

Along with frequency control, its sustained stochastic fluctuations have been studied for the power grid topologies in North America, Europe and Asia (Mureddu et al., 2016). It is analysed using the nonlinear dynamic swing equations in (Schäfer et al., 2018) which are modelled using non-Gaussian noise. Levy-stable and *q*-Gaussian distributions through superstatistics and its natural characteristics can help predict the chances of significant power grid events and set up isolated microgrids. Dynamic demand control (DDC) strategies (Tchuisseu et al., 2017) help control the household application switching using grid frequency. The algorithm consists of models of power generation systems and stochastic demand variations. The DDC protocol is derived to reproduce the statistical properties of frequency fluctuations, hence reducing its variance by delaying the smart switching devices.

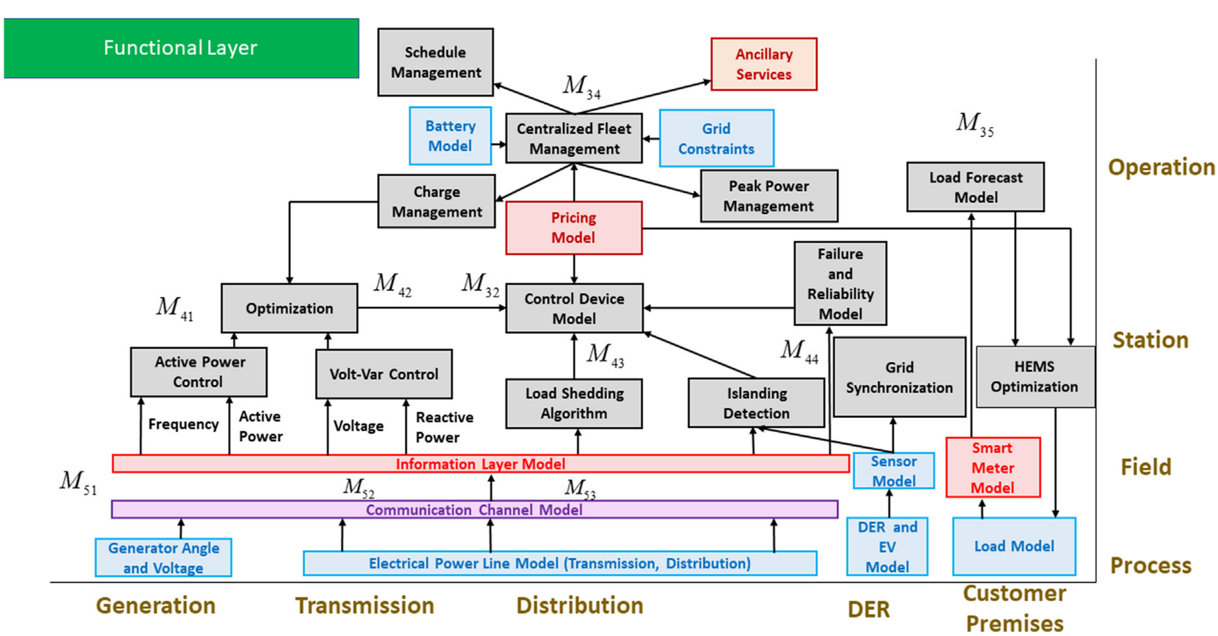

Fig. 6. Mapping on the SGAM functional layer (grey - functional layer, blue - component layer, red - information layer, purple — communication layer, brown - business layer).

Similar to the active power, reactive power plays an essential role in power system operations as it helps regulate the system voltage (Kundur et al., 1994), (Kothari, Nagrath and others, 2011) as shown in Fig. 6. Several instantaneous active and reactive power control has been discussed for the PWM converter (Ohnishi, 1991) and DFIG for wind power generation (Xu and Cartwright, 2006). Direct power control techniques has been discussed in (Malinowski et al., 2001; Malinowski et al., 2004) for PWM rectifiers using a virtual flux estimator and space vector modulation. The control techniques optimize and improve the reactive power losses and voltage profiles of the system using flexible AC Transmission Systems (FACTS) devices (Yoshida et al., 2000; Abdul-Rahman and Shahidehpour, 1993; Qiao et al., 2009). Several other reactive power control strategies have also been developed using expert systems (Cheng et al., 1988; Liu and Tomsovic, 1986) and hierarchical control schemes (Wen et al., 2004). FACTS is used for voltage control in the power system, which is modelled as a voltage source converter, connected to an energy storage device on one side and the power system on the other as given in (Rao et al., 2000). The conventional control of STATCOM using a PI controller and its comparison with the other state feedback control strategies has been described in (Rao et al., 2000). The control strategies to improve the power systems' transient stability using FACTS devices have been described in (Sadeghzadeh et al., 1998; Gronquist et al., 1995). Realization of distributed FACTS as a cost effective power flow control technique using distributed series impedance (DSI) and distributed static series compensator (DSSC) has been discussed in (Divan and Johal, 2005). It dynamically and statically changes the line impedance, thus controlling the power flow to improve the network's reliability. The FACTS devices have to be placed at optimal locations to maximize the power transmitted by the network. Thus in (Gerbex et al., 2001), four types of FACTS devices are modelled based on their operation, and their optimum location is found using a genetic algorithm validated on the IEEE 118-bus system. With the advent of advanced power electronic topologies and the increase in DC loads, the DC voltage bus will play an essential role in futuristic power grids. It is described in (Konishi et al., 2015) using a delayed feedback control methodology with an improvement in tracking the DC bus voltage.

The integration of renewable energy sources with the grid is a challenging task as the RES power output should match the grid parameters (frequency, voltage, and phase) as shown in Fig. 6. Hence, the integration is done using a phase-locked loop (PLL). However, using PLL's traditional grid synchronization algorithms have its disadvantages; hence, improved methodologies have been discussed in (Jaalam et al., 2016). The grid's synchronization performance is discussed concerning RES penetration, conversion characteristics, weather-conditions, control, and modelling techniques. The intelligent algorithms for grid synchronizations are also discussed under adverse grid conditions.

With the increasing penetration of RES in the grid, energy storage is becoming an essential part of the power system, enhancing the active and reactive power control functionalities. Various energy storage technologies and their role in evolving power system has been discussed in (Roberts and Sandberg, 2011; Ribeiro et al., 2001). Amongst them, battery energy storage is quite popular in power systems and the methods of assessing their economic viability has been discussed in (Divya and Ostergaard, 2009). The battery energy storage for peak load shaving, regulating the power flow control between RES and grid, providing ancillary services, improving the transmission and distribution feeder capability and smoothing of power and frequency fluctuations, while integrated to the grid along with solar and wind farms have been described in (Hill et al., 2012; Li et al., 2013). The mathematical models of various energy storage device models have already been described in the component layer, and their performance for various applications are described in (Hadjipaschalis et al., 2009; Luo et al., 2015). It is also essential to optimally size the energy storage systems based on the performance of the RES and the load requirements for power flow control strategies (Brekken et al., 2010; Mercier et al., 2009).

With the increasing penetration of RES and uncertain load demand of the rising population, it is essential to have strategies to safeguard from grid failures. Load-shedding is one of the techniques followed by distribution system operators in mismatched power generation and consumption, as shown in Fig. 6. Undervoltage load shedding has been discussed in (Taylor, 1992; Arnborg et al., 1997), taking into account the load dynamics and transients. Under-frequency load-shedding is a common practice for electric utilities to prevent frequency deviation from its setpoint in case of disturbance and protect the power system from dynamic instability and frequency collapse (Terzija, 2006), (You et al., 2003). The grid instability event can also be prevented using spinning reserve and economic dispatch (Moya, 2005). The system's dynamic response, for optimal load shedding levels, is accurately predicted using neural networks (NN) during an underfrequency load shedding scenario in (Mitchell et al., 2000).

Blackout causing cascading failure of power-grid, thus severely affecting its operation is described in (Wang et al., 2016), (Chen et al., 2005). Smart control strategies are described in (Wang et al., 2016) where the cases of traditional power systems and distributed generations are taken into account to mitigate cascaded failure. Cascaded failure in the power system causes blackouts in the system, which is a complex process to model mathematically. Complex mechanisms through cascading failure make it challenging to analyse the conventional power system techniques. Variety of mathematical and analytical tools for understanding the complicated mechanism of the cascading power grid failure have been discussed in (Guo et al., 2017). The analysis can be extended to examine the criticality of the power system blackout with the cascading events (Dobson et al., 2002) and occurrence of probabilistic failure due to the load demand (Dobson et al., 2005). The blackout and the cascading failure models in SGAM have been shown in Fig. 6. These mathematical models highlight the complex interaction between the power system components; hence the robustness and vulnerabilities of the power networks are systematically studied. It is also essential to study the events leading to cascading failure, dependent on various factors (Dobson et al., 2002). Robust synchronization of the generators is carried out to enhance the stability and provide robustness against structural failure of the grids. Spatial uniformity analysis of the generator locations in (Lee and Kim, 2017) suggests that synchronization operation is enhanced with the distribution uniformity of generators and provides robustness against temporal failures. The robust synchronization of the power plant and customers underlines the stable operation of the electric grids. In (Rohden et al., 2012), self-organized synchronization of decentralized power sources is studied under oscillatory networks. It is found that the decentralized grids are more robust to topological failures while being more sensitive to dynamic perturbations. A new class of distribution networks is discussed in (Farr et al., 2014) which can withstand damage and while healing rapidly with sustained repeated attacks with a modest increase in repair cost. The long term evolution and self-organization of power grids are studied in (Po et al., 2017). Here the evolving model of the power grid is explained along with the earthquake sandpile model. The analysis is conducted based on blackout magnitudes and inter-event waiting time. The models are tested on the IEEE 118-bus system, and proactive maintenance strategies are derived to drive power grids from self-organization to suppress blackouts.

Optimization techniques have widely been applied for smart grid planning and operation problems. With the power system deregulation and random load fluctuation and the integration of uncertain RES, many practical challenges have emerged. Hence, new optimization strategies are applied to improve the technical and economic efficiency of the smart grid. An overview of uncertainty modelling has been described in (Zubo et al., 2017) to quantify distributed generation (DG) impact on the assessment, operation, planning, and power flow. The analysis has been conducted under probabilistic loading conditions and reliability-oriented distribution network configuration to formulate procurement and bidding strategies in the electricity markets.

The uncertainty of the RES especially wind power generation forecast can be incorporated into power grid operation, dispatch and unit commitment planning as reviewed in (Makarov et al., 2011) along with its reactive power capabilities (Zou et al., 2011). Incorporating uncertainty in robust and stochastic optimization techniques can be an effective strategy for economic dispatch and unit commitment (Lorca and Sun, 2014; Constantinescu et al., 2010). The uncertainty of the RES failure can also be incorporated using swarm intelligence techniques (Kang et al., 2012) in power networks. DG scheduling to optimize the total cost has been described in (Zou et al., 2011), which includes capital, operation and maintenance, reliability and cost of deferred energy, considering its uncertainties and constrained reactive capabilities. The total generation cost is reduced by stochastic optimization incorporating the numerical weather prediction (Constantinescu et al., 2010) from the real wind speed data, thus optimizing active power loss and voltage deviation, due to the uncertain generator failures and variable load demand (Kang et al., 2012) under various operational constraints. The distributed generators' look-ahead schedule is formulated in (Makarov et al., 2011) based on the forecast data acquisition and prediction of grid balancing requirement for the given horizon, considering its failure uncertainty to formulate capacity and ramping requirements. Dynamic relationships across different stages are modelled using dynamic uncertainty sets (Lorca and Sun, 2014), which considers the temporal and spatial correlations of uncertainty to facilitate robust economic dispatch under the rolling horizon framework.

The uncertainty posed by the DG is counteracted by the optimal installation capacity of the energy storage devices and spinning reserves. The pumped energy storage capacity while considering dynamic security and economic operation (Brown et al., 2008) and spinning reserve requirement for errors in load forecast and outage has also been discussed in (Ortega-Vazquez and Kirschen, 2008). Energy storage has to be optimally placed in the grid so as to minimize the total wind power spillage (Atwa and El-Saadany, 2010). With the incorporation of the uncertainty from the DGs along with ESS, and controllable load active network distribution planning is very essential to minimize the overall investment and operational cost (Sedghi et al., 2015) while incorporating electric vehicles into the grid services (Su et al., 2014; Saber and Venayagamoorthy, 2011). The battery installation is planned based on their location, capacity, and power rating. The planning incorporates the uncertainty posed by DG in order to optimize the storage investment, operation and reliability cost. The charging and discharging schedule have been formulated to provide services like peak shaving, voltage regulation, and reliability enhancement of the grid. ESS is allocated accordingly to maximize the benefits to the DG and utility owner by accommodating the amount of spilled energy and minimizing the generation cost respectively (Atwa and El-Saadany, 2010), under high penetration of wind energy. The placement of energy storage devices in the power grid is essential, especially while ensuring overall economic operation. Non-parametric statistics have been used to analyse the inter-hour operational behaviour of energy storage at different locations in the grid (Panda and Das, 2020).

Optimal amounts of spinning reserves are accommodated based on the wind power generators' uncertainty in the grid. The decisions are taken incorporating the generators' random outages and possible errors in load and DG power forecast (Ortega-Vazquez and Kirschen, 2008). Charging and discharging control of electric vehicles (EVs) are scheduled based on uncertain charging time, SOC and start and end time to minimize the operational, transportation emission and battery degradation cost (Su et al., 2014; Saber and Venayagamoorthy, 2011). Pumped storage plant is integrated into the traditional power system to incorporate the stochastic load and renewable energy. It improves dynamic security to minimize the daily operational and installation cost based on the power and energy capacity (Brown et al., 2008).

When the interconnected smart grids face severe disturbances, the whole power network might be split into more than one "islanded" network, to preserve the balance between power generation and consumption. Hence, various aspects concerning the islanding of power grids have been discussed in (Liu and Liu, 2006). The three aspects discussed are - criteria for out of step conditions, islanding methodologies and load-shedding schemes. Various islanding scenarios of 13.8 kV distribution unit from the main-grid and its autonomous operation as microgrids are studied. The distributed generation based microgrid needs to sustain the angular stability under severe transient disturbances and voltage quality of the buses with fast reactive control. In (Katiraei et al., 2005), the technical viability of autonomous microgrid operation is studied using fast control of the electronically interfaced DG unit. The automatic phase-shift method for islanding detection is proposed in (Hung et al., 2003) which shows better results when compared to traditional islanding detection algorithms. Various anti-islanding measures have been described in (Vyas et al., 2017) along with the technical and financial implications. Some predictive approaches for islanding detection have been discussed for the solar inverters before the tripping of circuit breakers. Topology-based approach from network science is discussed in (Mureddu et al., 2016) to estimate the grid's stability by power balance.

Apart from control functionalities, the functional layer could be used to test several protection functions as well e.g.

- Differential protection (Kar et al., 2017),
- Over/under-voltage, over/under-frequency, rate of change of frequency (ROCOF) protection functions (Terzija et al., 2011; Järventausta et al., 2010; Timbus et al., 2010),
- Static and dynamic protection testing (Terzija et al., 2011; Järventausta et al., 2010; Timbus et al., 2010),
- Loss of mains (LOM) protection (Laverty et al., 2015; Roscoe et al., 2014) etc.

As a test case, two-stage strategies have been shown in (Adinolfi et al., 2015), comprising a midterm and a short-term controller. The control functionalities are:

- Midterm controller – Setpoint generation through constrained optimization using the forecast information (load, renewable generation forecast, weather), cost of energy (import, export, and production), constraints of each device (state of charge).
- Short-term controller – Keeping the microgrid's energy consumption over a specified period within a limit, as per the contractual agreement with the distribution system operator (DSO).

Optimal load distribution contributes to the efficient operation of microgrids in the smart grid environment. It can lead to minimal line congestion, as shown in Fig. 6. The study in (Zhou, Yang, Chen and Ding, 2014a) points out the deficiencies in the existing models where the optimal load distribution model is discussed, promoting the study of microgrid economics while achieving the intelligent power generation and distribution of the grid. Evolutionary algorithms are used to optimize the generation cost of the grid while complying with real-time constraints.

As per the study reported in (Coffele et al., 2012), the integration of two functionalities – adaptive protection and active network management (ANM) has been described in grid-connected and islanded modes. The ANM brings additional functionalities like power flow management, voltage control and loss minimization, thus improving power grid performance (Coffele et al., 2012). The ANM, especially the power flow management is framed as a constraint satisfaction problem (CSP) which has been applied to the microgrid for DG curtailment (Venturi et al.). Therefore, the functional layer's main challenges can be summarized as the efficient co-ordination of control, estimation, optimization, and protection functionalities keeping in mind the other layers' constraints and facilitating interoperability.

2.5. SGAM business layer

From the business context, high-level constraints and price inputs are incorporated within the local power control algorithms as described in (Roscoe et al., 2011), e.g.

- Maximum import/export power limits (penalty price or lower export price)
- Price of electricity import/export within normal limits
- Price for operating DGs at different output levels
- Price for making DG unit stand idle.

Different constraints from safety and operational perspective could be:

- Forecasting of load, generation, and weather
- Cost of energy import, export, and production
- Balance of each electric load and storage capacity
- Active and reactive power limits
- Thermal limits for lines.

Different constraints are imposed by different actors (TSO, DSO, supplier, consumer, data exchange, and service provider) from control, protection, and scheduling point of view from the business perspective. The regulatory functions for renewable energy source (RES) integration have been discussed in (Cambini et al., 2016) since integration requires installing new infrastructures and uncertainties for system reliability, security, and planning. The conflicting business interests amongst different actors are also integrated within the optimization framework, requiring various data from other layers. Therefore, the business perspectives are placed in the higher zones. Two different architectures as test cases have been demonstrated in (Adinolfi et al., 2015):

- Single busbar architecture where all controllable devices operate by a centralized controller. It is suitable for service type buildings like shopping malls, office, public buildings etc.
- Cluster architecture where a hierarchical structure of central and sub-controllers are all equipped with the same control intelligence.
- The global energy consumption e.g. huge cruise ships etc.

As we know that load forecasting plays an essential part in the planning and operation of power systems. The load forecasting is generally carried out using neural networks, as shown in (Park et al., 1991) from the smart meters' data, as shown in Fig. 7. Based on the load forecasting and dynamic pricing techniques, effective demand-side management (DSM) is implemented. Thus DSM is categorized into the following four categories (Palensky and Dietrich, 2011) and shown in Fig. 7:

- Energy efficiency (EE)
- Time of use (ToU)
- Demand response (DR)
- Spinning reserve (SR).

The dynamic pricing scheme as a part of DR is applied where the electricity price varies as per the time of the day with the schemes such as real-time pricing (RTP), time of use (ToU), critical peak pricing (CPP) which are described in (Palensky and Dietrich, 2011), (Khan et al., 2016). It is shown that the RTP scheme yields the best result in terms of improving the system reliability, reducing the generation cost along with the optimal utilization of the generation. DSM is applied to a general household, especially ToU and the corresponding data is collected and analysed in (Torriti, 2012; Gottwalt et al., 2011). The results are used by the utility for planning and designing a framework for incorporating uncertainty in DSM strategies (Gellings and Smith, 1989). DSM strategy is implemented as an optimization problem where the appliance scheduling is considered as binary decision variables to minimize the overall electricity consumption cost (Atzeni et al., 2012; Logenthiran et al., 2012), CO_2 footprint (Logenthiran et al., 2012), peak hourly load (Atzeni et al., 2012) and maximization of social welfare objective function (Samadi et al., 2012) with the involvement of energy storage devices, (Arteconi, Hewitt and Polonara, 2012, 2013; Atzeni et al., 2012)(Logenthiran et al., 2012), renewable energy technologies like solar (Matallanas et al., 2012) and wind power (Moura and De Almeida, 2010) and PHEV charging control (Vandael et al., 2012).

The consumers play an essential role to control their energy consumption pattern based on the price signals from the utilities, which is formulated using game-theoretic methods so that the revenue of the utilities and consumers reach a Nash equilibrium (Maharjan et al., 2013; Soliman and Leon-Garcia, 2014) with the reduction in the peak load (Nguyen et al., 2012; Mohsenian-Rad et al., 2010) using agent-based models (Broeer et al., 2014). Hence sufficient incentive and tariffs have to be developed for demand response in smart grid wholesale, retail markets (Vardakas et al., 2014; Deng et al., 2015; Balijepalli et al., 2011). The incentive-based demand response strategies are described in (Celik et al., 2017). These schemes reward end-users based on the reduction of energy usage and CO_2 emissions. The demand response scheduling algorithms are developed based on the consumers' lifestyle and appliance usage priority (Ma et al., 2016). The utility market can get real-time feedback on the implemented demand response strategy by monitoring hourly load usage patterns from pricing signals (Qian et al., 2013; Conejo et al., 2010) where a consistent monitoring helps in the improvement of these strategies. A robust load forecasting technique needs to be used based on classical statistics or artificial intelligence (AI) and machine learning (ML) techniques to schedule the household devices, as shown in Fig. 8. The loads are classified based on their consumption patterns. As discussed in (Beaudin and Zareipour, 2015), the customer's well-being and comfort are modelled from the load usage and the weather forecasting models. The analysis can also be conducted based on the consumer's inconvenience due to load scheduling in non-peak hours using a constant or a dynamic penalty function in the optimization system. Electrical energy in residential areas is also managed by coordinating smart homes with intelligent DSM strategies (Celik et al., 2017). At first, the consumer load is modelled

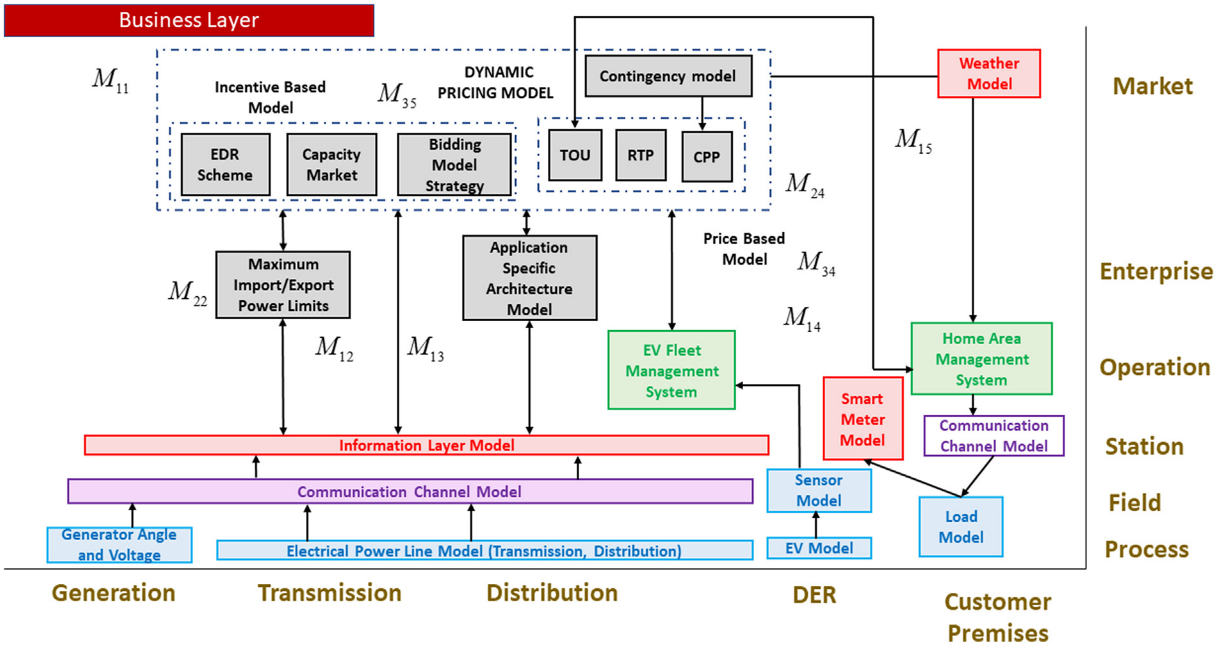

Fig. 7. Mapping on the SGAM business layer (grey - business layer, blue - component layer, red - information layer, green - functional layer, purple - communication layer).

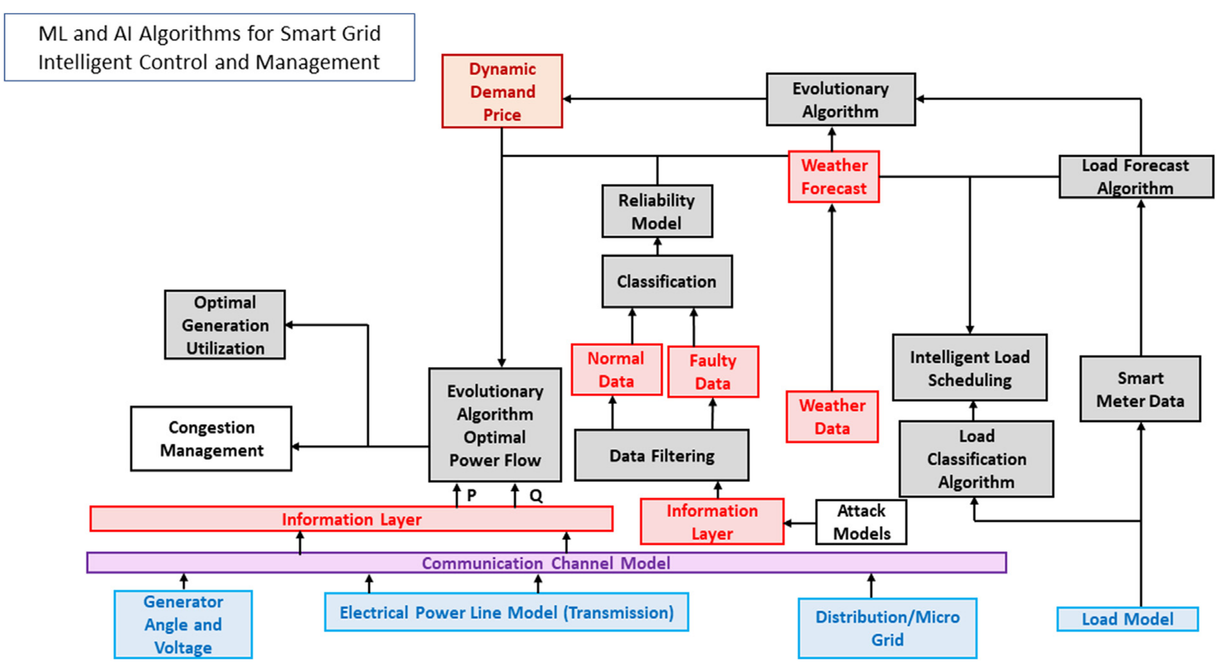

Fig. 8. AI and ML applications in future smart grid research (grey - ML/AI functions, blue -component layer, red - information layer, purple - communication layer, brown – business layer).

using bottom-up and top-down approaches. Then decentralized coordination optimization problem is formulated based on various DSM approaches. The result showed improvement in peak demand and cost reduction and the limited impact on customers' comfort.

PHEVs can also be used collectively to enhance the business model of utility companies, as shown in Fig. 7. The optimal control strategy for electric vehicle aggregator is used as a criterion using regulation price and charging cost, as discussed in (Hota et al., 2014). Electric vehicles are an essential part of the smart grid as they can take part in grid balancing services, thus regulating the grid frequency. However, higher penetration in the distribution level can have an adverse impact on the grid. Hence smart charging techniques will be required as discussed in (Hu et al., 2016). The advantages and disadvantages of various charging control strategies for PHEVs are described in (Hu et al., 2016) which include transactive control, centralized control and price control. Centralized control scheme showed the best results for optimal scheduling. Optimal charging schedule is generated using driving patterns and forecasted electricity price. Implementing transactive control is essential to provide more controllability to the end-users along with the scalability of implementing in a vast electric vehicle network. Price control is an attractive method for fleet management, where the charge controller decreases the rate of charging during the peak period and vice versa during the non-peak period.

The role of PHEVs, modelled as multi-agent systems, while participating in the electricity market and providing ancillary services for the grid, has been described in (Hota et al., 2014). Market bidding strategies for the EV aggregators have been formulated using heuristic reinforcement learning approach and genetic algorithm as reviewed in (Hota et al., 2014) to maximize the benefits to the involved stakeholders. Ancillary services to the grid can also be provided by self-organized coalitions with the power plants while trading active power with the grid (Nieβe et al., 2012), frequency bandwidth modelling of operating loads while maintaining the quality of service (QoS) (Barooah et al., 2015) and exploring the spatio-temporal demand response strategies integrated with the power system models for maximizing the economic benefits (Ma et al., 2013).

The business layer's primary challenge is to incorporate the expert knowledge and business constraints from the immediate next layer – functional layer that holds the control, estimation, optimization and protection modules. The functional layer then accesses the available data (information layer) and interacts with the component layer through the communication layer. Thus, the whole process could be viewed as a top-down design approach for the effective co-ordination of different SGAM layers in diverse zones and domains.

3. Cybersecurity challenges in future smart grids

With the advent of smart grid technologies while accommodating DERs and PHEVs, improved sensing, communication, and control strategies are required. Hence, it increases the vulnerability of smart grids to cyber-attacks which can alter the data used for the estimation and control of grid operations, thus leading to severe maloperations. The SGAM has been used for cyber-security requirements and risk assessment in (Neureiter et al., 2016), (Langer et al., 2016). Like the NIST model, several other smart grid standards are compared with the SGAM for cyber-security in (Ruland et al., 2017) while incorporating global perspectives (Leszczyna, 2018). Security of smart meters is essential as the incorrect readings can lead to incorrect billing, hence causing a significant effect on power economy. Access to the smart meter data, as shown in Fig. 8, can expose users' household appliance usage pattern, from which the lifestyle can be ascertained using intelligent algorithms. Power system estimation models are essential for predictive maintenance of smart grids. Introduction of false data into the model can cause system grid instability and financial gain for the attacker. As described in (Wang and Lu, 2013), three smart grid security levels have been described: availability, integrity, and confidentiality. Several classification strategies of the attacks have been performed, and their effects on several communication layers are described viz. physical layer, media access control (MAC) layer, network and transport layer and application layer. Effects of cyber-attacks on data integrity and confidentiality have also been described in detail in (Wang and Lu, 2013).

A security model for the exposure of smart grids in the evaluation framework is introduced in (Hahn and Govindarasu, 2011) to explore various privileged states and viable paths exploited by the attacker. Information based performance metric is used to check the effectiveness of the security measure. The security mechanisms developed in (Hahn and Govindarasu, 2011) can protect several information objects present in the smart grid. The vulnerabilities of the information objects have been simulated, and their effects are demonstrated with the defined performance metrics. Sensors and actuators also play an essential role in service and management offering in the Industry 4.0 paradigm, leading to the development of heterogeneous infrastructure with various technological and security solutions. Thus, their proper deployment framework is discussed in (Batista et al., 2017), making the system more robust and reliable.

Cyber-physical interactions quantifying attacks on power networks have been described in (Sridhar et al., 2012) along with the respective countermeasures. At first, the risk assessment methodology is adopted incorporating cyber and physical attacks, including the analysis and mitigation using probabilistic grid failure deduced from the attack trees. Each component of the smart grid - generation, transmission and distribution has been described along with the cyber vulnerabilities associated with their control functions. In the generation side, cyber-attacks can change the setpoints for the governor and automatic voltage regulator (AVR), thus affecting the frequency and active power control. Cyber-attacks on transmission control side can affect the state estimation algorithms, FACTS devices operation and wide area monitoring systems (WAMS). The cyber-attacks on the distribution systems can affect the load shedding and DSM strategies. Once the effects are studied, supporting methodologies are adopted to detect the cyber-attacks and mitigate them. Emerging research challenges on cybersecurity on the smart grid are also discussed in (Sridhar et al., 2012), including risk modelling and mitigation algorithms, coordinated attack defence, advanced metering infrastructure (AMI) security, trust management, attack attribution and incoming data validation. Mathematical modelling of these cyber-attacks helps in designing efficient mitigation strategies. Petri net-based modelling is discussed in (Chen et al., 2011), where they offer more flexibility and expressiveness than the traditional attack trees. Unification of several cyber-attack Petri-net models has been discussed using model descriptive language. The research reported in (Giani et al., 2013) characterizes irreducible cyber-attacks that compromises the power meters, along with the mitigation strategy.

The nature of the cyber-attack requires human judgement for its detection. Machine learning algorithms have been deployed in (Hink et al., 2014) to discriminate various cyber-attacks from the faulty data as shown in Fig. 8. Three classification schemes are discussed in (Hink et al., 2014) to help the operators decide the smart grid's normal operations. A new type of cyber-attack called stealth attack is described in (Esmalifalak et al., 2017), which cannot be detected using the state estimation techniques. The attack is statistically distinguished using supervised learning of a labelled data with distributed support vector machine.

4. Further research directions

In the future, an increase in total energy consumption is forecasted, along with a decrease in power generation from fossil fuel. Moreover, a rapid increase and decrease in the deployment of renewable and nuclear energy resources have also been discussed. The comparative analysis of energy resource and consumption is performed based on the data and the forecast in the year 2012 and 2050 (Simard, 2013) as shown in Fig. 9 and Fig. 10, respectively. Predictions suggest that a substantial amount of energy in 2050 will be generated by renewable energy while there will be a subsequent reduction in fossil fuel generation. However, the load consumption and the power losses will increase rapidly for different end-use applications like industry, building and transport. There needs to be a drastic change in energy flow architecture and the expected functionalities of the power grid, which is summarized in the following subsections.

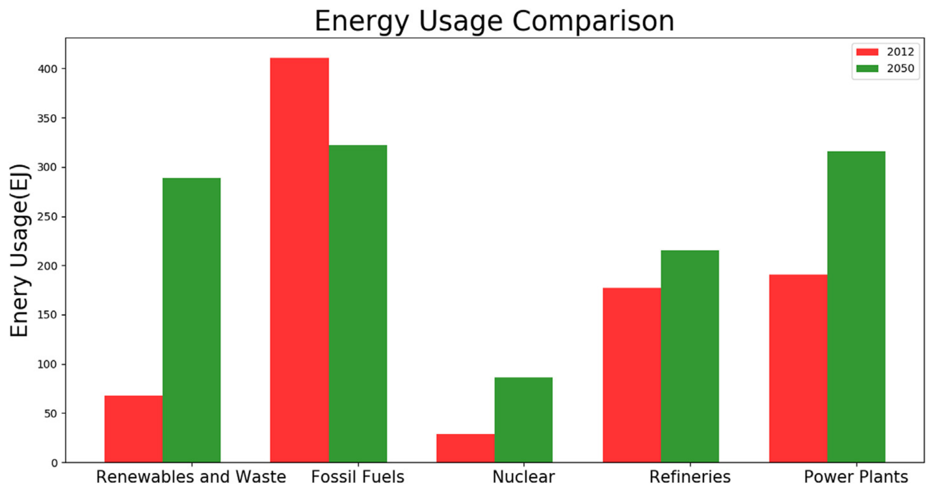

Fig. 9. Energy resource comparison in 2012 and 2050.

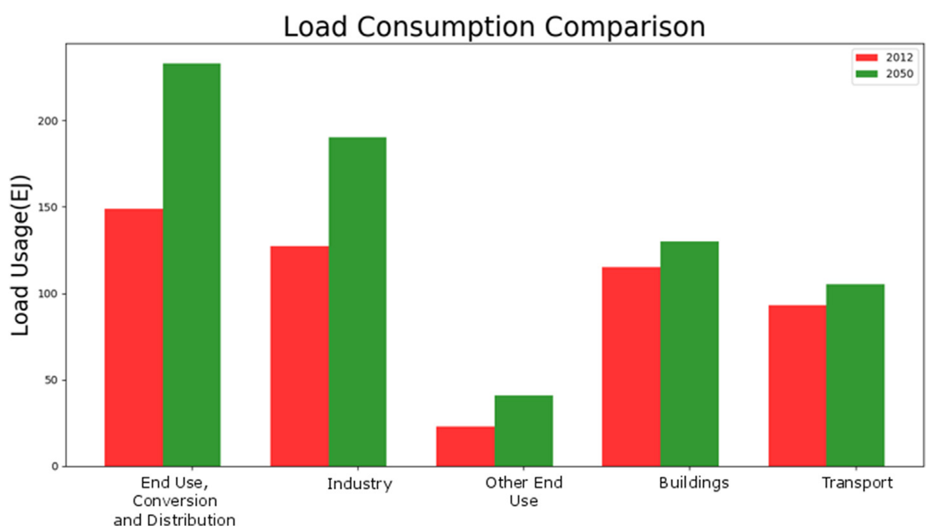

Fig. 10. Load consumption comparison in 2012 and 2050.

4.1. Autonomous power systems

The power system is expected to have autonomous features as more advanced functionalities are incorporated into it. Some expected autonomy of the future smart grids can be described as follows:

4.1.1. Self-optimizing

The self-optimization strategy for the data and web grids (Gounaris et al., 2008; Schintke et al., 2003) has been formulated while the components are running concurrently. A similar strategy can be applied for the power dispatch of energy systems based on the random load fluctuations and environmental conditions, thus optimizing the whole system's performance concerning the goals as shown in Fig. 8. Different zones of control can be identified based on a dynamic boundary using data clustering techniques hence prioritizing the control strategies. Similar algorithms can be deployed to identify high energy consumption areas and islanding algorithms based on the RES penetration levels.

4.1.2. Self-healing

The self-healing strategy for power grids has been described in (Wang et al., 2015; Zidan and El-Saadany, 2012; Eriksson et al., 2014) using multi-agent systems. In (Eriksson et al., 2014), the multi-agent systems in distribution automation solutions have been applied based on IEC 61850 standard, for fault location identification, isolation and service restoration in the grid using an undirected weighted graph. Self-healing strategy using multi-layer control structure architecture has been discussed in (Wang et al., 2015; Zidan and El-Saadany, 2012). Various power grid reconfigurable strategies have been discussed like controlling the active elements of the network distributed generators (DGs) and controllable loads (CLs) (Golshannavaz et al., 2014), changing the mode of operation of the microgrid during islanded and grid connected mode as current and voltage source respectively while implementing the P/Q strategies of the inverter for load sharing (Rodriguez et al., 2011) along with hardware in loop (HIL) strategies in (Qi et al., 2011) with embedded intelligence and coordination schemes at both local and systems level. Functionalities like reconfigurable control schemes for inverters in islanded and grid-connected mode (Rodriguez et al., 2011), fault-tolerant framework through intelligent coordination (Qi et al., 2005), strategies concerning identification and prevention of propagation of attacks (Qi et al., 2011) and control of the active elements in the network using optimal operational scheduling framework (Golshannavaz et al., 2014) can be combined with the multi-agent strategy described above to optimize the transition time for the loads not receiving power in the case of power link failure.

4.1.3. Self-control

The primary objective of self-healing control is to operate the grid without the power loss to loads due to abnormalities. Automatic anticipation and response to disturbances have been discussed in (Liu et al., 2012) while optimizing the grid performance using a “2-3-6” control architecture. The smart grid control problem can be simplified using the “Web of Cells” concept (Dhulst et al., 2015; Heussen et al., 2015; Martini et al., 2017; Guillo-Sansano et al., 2016) by confining it to a geographical area defined by well-defined grid boundaries. It is found that the stability of the system is enhanced using the decentralized control concept defined in (Dhulst et al., 2015). The controller conflict solution using use case management has been described in (Heussen et al., 2015). The distributed and decentralized strategy can be extended for energy dispatch problems when a new controllable generation source is added thus making it self-adjustable based on the existing loading and seasonal conditions from historical load data and weather conditions as shown in Fig. 8.

4.2. Coupled voltage and frequency control

As we have seen in the component layer, the frequency and voltage fluctuations depend on the load variability. The coupled frequency and voltage control based on random load fluctuations are solved using the model derived in (Chiang et al., 1993) and in (Heussen et al., 2015) to mitigate voltage harmonics. The frequency control by regulating the turbine input and the generator’s exciter input can have an overall impact on the load voltage of a system as given in (Chiang et al., 1993). The inertia of the system due to random load changes is drastically reduced by incorporating more inverter fed renewable energy resources. Hence an overall decoupling control strategy can be developed for voltage stability of the grid during frequency deviations and vice versa with the inclusion of low inertia dynamics of an inverter-based system. The coupled voltage and frequency control can also be applied based on the variety of loads classified from smart meter data, as shown in Fig. 8, and the strategy can be tested accordingly.

4.3. Regulatory policy for renewable energy-based virtual inertia

The physical inertia of the prime mover is significant in the power system dynamics, and its relevance is described in (Tielens and Van Hertem, 2016). Several methods to emulate inertia has been replicated for RES by incorporating rotating mass to DFIG shaft and supercapacitor connected to the DC-link of the inverter via DC-DC converters (Arani and El-Saadany, 2012), virtual synchronous generator (Alipoor et al., 2014), distributed storage in isolated power systems (Delille et al., 2010) and novel droop controller for the inverters (Soni et al., 2013). Since there are abundant strategies for compensating the inertia in the power systems, regulatory policy needs to be defined for the best strategy to emulate virtual inertia based on grid conditions and uncertain weather conditions as shown in Fig. 8.

4.4. Resolving various control conflicts

Since smart grid consists of 5 different layers as described previously and each layer has its own objectives which might conflict with others. Previous works on solving conflicting scenarios through multi-objective optimization has been described in the case controller tuning for power systems (Panda and Yegireddy, 2013), coordination between local and supervisory power system stabilizers using multi-agent systems (Ni et al., 2002) using LMI based H_∞ controllers. The solution method of the multi-objective problems of the component layer can be extended to communication and business layers by incorporating their objectives. There may be conflicting requirements between the grid and market operating points which are resolved using consumer and network agents (Nguyen et al., 2013) while minimizing the energy consumption cost and maximizing the energy resource utilization (Salinas et al., 2012). These strategies can also be extended to resolve conflict between various control decisions that arise, as the smart grid will have a large number of controllable and diverse type of interconnected devices with various dynamical characteristics.

4.5. Analysing the stability and robustness of the smart grid

With various devices in the grid with their typical dynamical behaviors, the smart grid becomes an extremely complex system. Hence it is essential to derive a metric which defines its robustness and stability. Various works have been discussed in the field of stability and robustness of complex systems (Zhang and Chi, 2015; Gribble, 2001) applicable to similar ecological models (Cohenpb and Charles, 1985; Allesina and Tang, 2012) to predict the system’s failure modes and dynamics based on small perturbations. Several interactions have been defined, which tends to stabilize and destabilize the complex networks (Allesina and Tang, 2012) where strong or weak couplings have been identified accordingly (Gribble, 2001). Robustness analysis for power system has been performed in (Zhang and Chi, 2015), using percentage of unserved nodes (PUN) theory, based on the number of the critical links not causing damage. The stability and robustness analysis can be extended to a complex smart grid model to highlight the coupling between several network components, which can stabilize and destabilize the whole system.

4.6. Inclusion of device nonlinearity in smart grid functionalities

The smart grid simulation modelling has been mostly based on linear models while ignoring the nonlinearity of the system components. Previous works incorporating the system nonlinearity has been performed in (Karlsson and Hill, 1994; Dö;rfler, Chertkov and Bullo, 2013). The nonlinearity in the load models derived in (Karlsson and Hill, 1994) is included in the frequency control problems, and the stability assessment has been performed accordingly. The nonlinearity of the devices can be extended to modify the existing functionalities and define its stability and robustness criteria.

4.7. Using market pricing signal for controlling grid parameters

In the business layer, several works have been carried out on energy pricing formulation. The pricing signal is extended to the functional layer for several smart grid functionalities. Ancillary services addressing the voltage control have been discussed in (Madureira and Lopes, 2012; Zhong et al., 2004) using optimal power flow (OPF) formulation and distributed generation involvement. Demand response model has been described in (Venkatesan et al., 2012), considering the rationality of different consumers and the day ahead pricing scenario. The price model derived in the above scenarios can be used for frequency control, and the optimal operating point can be defined using evolutionary optimization algorithms, as shown in Fig. 8.

4.8. Grid reliability definition with the inclusion of ICT

With the integration of the ICT in the smart grid technology, it is essential to assess the operational reliability of the whole grid. The architectural paradigm to integrate these resources in the grid has been defined in (Moslehi and Kumar, 2010) while incorporating the impact of harsh environmental conditions, reliability and latency requirements, packet errors and variable link capacity and resources constraints like energy, memory and processing as described in (Gungor et al., 2010). The study can be extended to check the impact on the grid's energy markets and voltage and frequency stability. The reliability model can be built upon the input data obtained by classifying normal operation data from faulty data, as shown in Fig. 8.

4.9. Optimal grid operation during energy trading

Due to an increase in various independent stakeholders involved in energy generation, there has been a rise in the number of prosumers. Instead of procuring the utility suppliers' energy, the prosumers can trade energy at lower prices whose market design (Long et al., 2017; Zhang et al., 2017) and incentive schemes (Morstyn et al., 2018) have also been proposed. The internal pricing model for peer-to-peer trading is formulated considering the variability in supply and demand. It also incorporates distributed energy resources like electric vehicles (Alvaro-Hermana et al., 2016) and mobility patterns of the user using an aggregator and solar PV (Liu et al., 2017). The frequency and voltage dynamics with energy exchange along with reliability and stability studies can be conducted for this application. Evolutionary optimization algorithms for effective energy utilization and congestion management can be utilized during energy trading, as shown in Fig. 8.

4.10. Competition between energy sources

As smart grid promotes competition between several stakeholders, there is also a competition amongst energy generation and storage resources to meet the grid requirements (Clastres, 2011). Several studies have been conducted based on wind, combined cycle gas turbine plant and compressed air storage in (Greenblatt et al., 2007) and the selection strategy has been framed based on the least dispatch expenditure. This problem can be extended to include other energy sources, storage and to formulate other operational metrics for scheduling these resources for grid requirements.

4.11. Optimal cybersecurity architecture selection for smart grid application

Since a secure cyber network helps in the efficient performance of smart grids, various combinations of hierarchical architectures need to be explored based on data reliability. Several works on security technology (Metke and Ekl, 2010) and cyber-physical security testbeds have been defined in (Hahn et al., 2013), which can play a vital role in the grid's control performance, affecting the latency rates between the sensors and the controllers. Thus, a metric can be defined to select the best cyber-secure architecture to ensure the grid's optimal and stable performance.

4.12. Integration of energy volatility with the market

Several methods have been used to predict the volatility of the financial markets (Poon and Granger, 2003) using univariate and multivariate statistical models (Wang and Wu, 2012) by integrating high-frequency intraday data into modelling and forecasting (Andersen et al., 2003). These concepts can be extended to predict the volatility of environmental and load demands.

4.13. Demand side management based on customer lifestyle

As discussed in the business layer, demand response strategies play an essential role in reducing energy consumption while optimizing the overall economic performance. The impact on the energy demand based on the consumers' lifestyle has been defined in (Korjenic and Bednar, 2011; Beaudin and Zareipour, 2015). Machine learning algorithms can be used to identify consumers having similar lifestyles based on their daily energy consumption. These algorithms are useful for planning the tariff rate for various clusters of consumers. With energy democratization (Thompson and Bazilian, 2014; Szulecki et al., 2015), this strategy helps private energy companies formulate their business plan for a specific customer set. Intelligent load scheduling strategy can be developed for demand-side management to include renewable energy resources, based on the weather forecast data, as shown in Fig. 8.

4.14. Scheduling renewable energy dispatch based on 'just-in-time' strategy

Due to the increased focus of using solar and wind energy for power generation, there is an increasing number of prosumers. With the abundance of energy consumption data in the modern time, various data analytics techniques can help the prosumers schedule grid energy dispatch based on the grid conditions. The concept is analogous to the 'just-in-time' philosophy in supply chain management (Sugimori, Kusunoki, Cho and UCHIKAWA, 1977; Sakakibara et al., 1997) where production planning is done based on real-time customer demand.

5. Conclusions

This paper reviews the existing concepts of integrated mathematical and statistical modelling of the SGAM layers and also puts forward new ideas to materialize such complex system simulations for efficient modelling, control, optimization, diagnostics and analytics of future smart grid. The components in each layer are modelled according to a 2D matrix-like structure of domains and zones. The existing research in power networks and its economics, control, communication, and cybersecurity are explored to consolidate mathematical models for different smart grid components. Appropriate works can be followed up to simulate the smart grid systems and study their coordinated dynamical behaviour.

Since the smart grid technology is evolving rapidly, we will require innovative solutions to tackle the increasing load consumption by penetrating more renewable energy resources in the smart grids while tackling its intermittency by ensuring minimal usage of fossil fuel-based power generation that causes severe environmental damage. Hence, a coordinated view of the control, optimization, and data analytics problems have been discussed in this paper, mostly an extension of the SGAM model and similar solution strategies adopted from other complex smart grid systems. Several open research challenges in smart grid modelling and simulation, e.g. cybersecurity aspects, will help future simulation and modelling engineers design accurate or uncertain cyber-physical system models for robust smart grid system design with more renewable energy penetration and interoperable solutions with diverse components while meeting the communication, information, functional and business objectives and technological constraints.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgement

SD was partially supported by the ESIF ERDF Cornwall New Energy (CNE), project number: 05R16P00282 and also the ERDF Deep Digital Cornwall project number: 05R18P02820.

Appendix

Items in each SGAM layer in various domain and zones (2) are given below.

A1. SGAM Component Layer

Elements of the components layer are listed as ($l = Comp$):

M_{41} = {sensor system model in the power plant generation}
M_{42}= M_{43}={protective switching based on reliability model}
M_{61} = {dynamic model of the power plant, synchronous machine model}
M_{62} = {magnetic modelling of power transformers, transmission line model}
M_{63} = {magnetic model of distribution transformers, distribution line model}
M_{64} = {electric vehicle battery model, wind turbine model, PV model, converter model, induction generator model, flywheel storage devices, fuel cell generation}
M_{65} = {static load, dynamic load, statistical regression load model}.

A2. SGAM Communication Layer

The elements of the communication layer are listed as follows ($l = Comm$):

$M_{52} = M_{53} = M_{54}$= {random packet drop/delay model, deterministic channel model, data traffic noise model, statistical communication channel model}
M_{55} = {smart meter communication system model}
$M_{32} = M_{33} = M_{34}$ = {random packet drop model between distributed controllers}
M_{35} = {controller to HEMS random packet drop model}.

A3. SGAM Information Layer

The elements of the information layer are listed as follows ($l = I$):

$M_{31} = M_{32} = M_{33} = M_{34}$ = {cloud storage model, data filtering algorithms, data encryption algorithms, synchronized data collection model, event-based data collection model, cyber-attack models}
M_{35} = {smart meter data compression model}
$M_{41} = M_{42} = M_{43}$ = {transmission system state estimation algorithms, distribution state estimation algorithms}.

A4. SGAM Functional Layer

The elements of the functional layer are listed as ($l = F$):

$M_{51} = M_{52} = M_{53}$ = {differential protection, static and dynamic protection, loss of mains (LOM) protection, overvoltage, over-frequency, under-frequency, rate of change of frequency (ROCOF) protection}
M_{34} = {centralized fleet management system, charge control system for RES battery storage}
$M_{41} = M_{42} = M_{43} = M_{44}$ = {frequency control, voltage control, load shedding algorithm, islanding detection, grid synchronization algorithm}
M_{35} = {load forecasting model, home energy management system model}
M_{32} = {FACTS device model, component wise reliability models}.

A5. SGAM Business Layer

The elements of the business layer are listed as ($l = B$):

M_{11} = {operational and fuel cost}
$M_{12} = M_{13}$ = {transmission and distribution capital and maintenance cost}
M_{14} = {price for operating DGs, the price of DG curtailment}
M_{15} = {incentive based tariff, price-based tariff}
M_{22} = {maximum import/export power limits, energy arbitrage}
M_{24} = {application specific architecture, single busbar cluster}
M_{35} = {demand response and pricing strategies for the different consumer}
M_{34} = {cost of energy import, export and production, balance of each electric load and storage capacity}.

CRediT author statement

Deepak Kumar Panda: Methodology, Validation, Investigation, Data Curation, Writing - Original Draft, Visualization; **Saptarshi Das:** Conceptualization, Resources, Writing - Review & Editing, Supervision, Project administration, Funding acquisition.

References

Abbasy, N.H., Ismail, H.M., 2009. A unified approach for the optimal PMU location for power system state estimation. IEEE Trans. Power Syst. 24 (2), 806–813.
Abdin, E.S., Xu, W., 2000. Control design and dynamic performance analysis of a wind turbine-induction generator unit. IEEE Trans. Energy Convers. 15 (1), 91–96.
Abdul-Rahman, K., Shahidehpour, S., 1993. A fuzzy-based optimal reactive power control. IEEE Trans. Power Syst. 8 (2), 662–670.
Adinolfi, F., Burt, G.M., Crolla, P., D'Agostino, F., Saviozzi, M., Silvestro, F., 2015. Distributed energy resources management in a low-voltage test facility. IEEE Trans. Ind. Electron. 62 (4), 2593–2603.
Aditya, S., Das, D., 1999. Application of battery energy storage system to load frequency control of an isolated power system. Int. J. Energy Res. 23 (3), 247–258.
Ahmad, F., Rasool, A., Ozsoy, E., Rajasekar, S., Sabanovic, A., Elitas, M., 2017. Distribution system state estimation-A step towards smart grid. Renew. Sustain. Energy Rev. 81, 2659–2671.
Albano, M., Ferreira, L.L., Pinho, L.M., 2015. Convergence of Smart Grid ICT architectures for the last mile. IEEE Transactions on Industrial Informatics 11 (1), 187–197.
Ali, E., Abd-Elazim, S., 2011. Bacteria foraging optimization algorithm based load frequency controller for interconnected power system. Int. J. Electr. Power Energy Syst. 33 (3), 633–638.
Alipoor, J., Miura, Y., Ise, T., 2014. Power system stabilization using virtual synchronous generator with alternating moment of inertia. IEEE Journal of Emerging and Selected Topics in Power Electronics 3 (2), 451–458.
Allesina, S., Tang, S., 2012. Stability criteria for complex ecosystems. Nature 483 (7388), 205–208.
Alvaro-Hermana, R., Fraile-Ardanuy, J., Zufiria, P.J., Knapen, L., Janssens, D., 2016.

Peer to peer energy trading with electric vehicles. IEEE Intelligent Transportation Systems Magazine 8 (3), 33–44.
Andersen, T.G., Bollerslev, T., Diebold, F.X., Labys, P., 2003. Modeling and forecasting realized volatility. Econometrica 71 (2), 579–625.
Andrén, F., Strasser, T., Rohjans, S., Uslar, M., 2013. Analyzing the need for a common modeling language for Smart Grid applications. In: Industrial Informatics (INDIN), 2013 11th IEEE International Conference on, pp. 440–446.
Angioni, A., Lu, S., Hooshyar, H., Cairo, I., Repo, S., Ponci, F., Della Giustina, D., Kulmala, A., Dedè, A., Monti, A., others, 2017. A distributed automation architecture for distribution networks, from design to implementation. Sustainable Energy, Grids and Networks 15, 3–13.
Arani, M.F.M., El-Saadany, E.F., 2012. Implementing virtual inertia in DFIG-based wind power generation. IEEE Trans. Power Syst. 28 (2), 1373–1384.
Arghandeh, R., Pipattanasomporn, M., Rahman, S., 2012. Flywheel energy storage systems for ride-through applications in a facility microgrid. IEEE Transactions on Smart Grid 3 (4), 1955–1962.
Arnborg, S., Andersson, G., Hill, D.J., Hiskens, I.A., 1997. On undervoltage load shedding in power systems. Int. J. Electr. Power Energy Syst. 19 (2), 141–149.
Arteconi, A., Hewitt, N.J., Polonara, F., 2012. State of the art of thermal storage for demand-side management. Appl. Energy 93, 371–389.
Arteconi, A., Hewitt, N.J., Polonara, F., 2013. Domestic demand-side management (DSM): role of heat pumps and thermal energy storage (TES) systems. Appl. Therm. Eng. 51 (1–2), 155–165.
Atwa, Y.M., El-Saadany, E., 2010. Optimal allocation of ESS in distribution systems with a high penetration of wind energy. IEEE Trans. Power Syst. 25 (4), 1815–1822.
Atzeni, I., Ordóñez, L.G., Scutari, G., Palomar, D.P., Fonollosa, J.R., 2012. Demand-side management via distributed energy generation and storage optimization. IEEE Transactions on Smart Grid 4 (2), 866–876.
Azimi-Sadjadi, B., 2003. Stability of networked control systems in the presence of packet losses. In: 42nd IEEE International Conference on Decision and Control (IEEE Cat. No. 03CH37475), pp. 676–681.
Balijepalli, V.M., Pradhan, V., Khaparde, S., Shereef, R., 2011. Review of Demand Response under Smart Grid Paradigm, pp. 236–243. ISGT2011-India.
Barbierato, L., Estebsari, A., Bottaccioli, L., Macii, E., Patti, E., 2020. A distributed multimodel cosimulation platform to assess general purpose services in smart grids. IEEE Trans. Ind. Appl. 56 (5), 5613–5624.
Barooah, P., Buic, A., Meyn, S., 2015. Spectral decomposition of demand-side flexibility for reliable ancillary services in a smart grid. In: 2015 48th Hawaii International Conference on System Sciences, pp. 2700–2709.
Batista, N., Melicio, R., Mendes, V.M.F., 2017. Services enabler architecture for smart grid and smart living services providers under industry 4.0. Energy Build. 141, 16–27.
Beaudin, M., Zareipour, H., 2015. Home energy management systems: a review of modelling and complexity. Renew. Sustain. Energy Rev. 45, 318–335.
Beaufays, F., Abdel-Magid, Y., Widrow, B., 1994. Application of neural networks to load-frequency control in power systems. Neural Network. 7 (1), 183–194.
Benitez, I., Quijano, A., Diez, J.-L., Delgado, I., 2014. Dynamic clustering segmentation applied to load profiles of energy consumption from Spanish customers. Int. J. Electr. Power Energy Syst. 55, 437–448.
Bevrani, H., Shokoohi, S., 2013. An intelligent droop control for simultaneous voltage and frequency regulation in islanded microgrids. IEEE Transactions on Smart Grid 4 (3), 1505–1513.
Bolund, B., Bernhoff, H., Leijon, M., 2007. Flywheel energy and power storage systems. Renew. Sustain. Energy Rev. 11 (2), 235–258.
Borunda, M., Jaramillo, O., Reyes, A., Ibargüengoytia, P.H., 2016. Bayesian networks in renewable energy systems: a bibliographical survey. Renew. Sustain. Energy Rev. 62, 32–45.
Brekken, T.K., Yokochi, A., Von Jouanne, A., Yen, Z.Z., Hapke, H.M., Halamay, D.A., 2010. Optimal energy storage sizing and control for wind power applications. IEEE Transactions on Sustainable Energy 2 (1), 69–77.
Broeer, T., Fuller, J., Tuffner, F., Chassin, D., Djilali, N., 2014. Modeling framework and validation of a smart grid and demand response system for wind power integration. Appl. Energy 113, 199–207.
Brown, P.D., Lopes, J.P., Matos, M.A., 2008. Optimization of pumped storage capacity in an isolated power system with large renewable penetration. IEEE Trans. Power Syst. 23 (2), 523–531.
Bui, N., Castellani, A.P., Casari, P., Zorzi, M., 2012. The internet of energy: a web-enabled smart grid system. IEEE Network 26 (4), 39–45.
Cambini, C., Meletiou, A., Bompard, E., Masera, M., 2016. Market and regulatory factors influencing smart-grid investment in Europe: evidence from pilot projects and implications for reform. Util. Pol. 40, 36–47.
Carrasco, J.M., Garcia Franquelo, L., Bialasiewicz, J.T., Galván, E., Portillo Guisado, R.C., Martin Prats, M. de los Á., León, J.I., Moreno-Alfonso, N., 2006. Power-electronic systems for the grid integration of renewable energy sources: a survey. IEEE Trans. Ind. Electron. 53 (4), 1002–1016.
Celik, B., Roche, R., Suryanarayanan, S., Bouquain, D., Miraoui, A., 2017. Electric energy management in residential areas through coordination of multiple smart homes. Renew. Sustain. Energy Rev. 80, 260–275.
Cen-CENELEC-ETSI Smart Grid Coordination Group, 2012. Smart grid reference architecture [online] Available at: https://ec.europa.eu/energy/sites/ener/files/documents/xpert_group1_reference_architecture.pdf.
Cervin, A., Henriksson, D., Lincoln, B., Eker, J., Arzen, K.-E., 2003. How does control timing affect performance? Analysis and simulation of timing using Jitterbug and TrueTime. IEEE Contr. Syst. Mag. 23 (3), 16–30.
Cervin, A., Arzen, K.-E., Henriksson, D., Lluesma, M., Balbastre, P., Ripoll, I., Crespo, A., 2006. Control loop timing analysis using TrueTime and Jitterbug. In: 2006 IEEE Conference on Computer Aided Control System Design, 2006 IEEE International Conference on Control Applications, 2006 IEEE International Symposium on Intelligent Control, pp. 1194–1199.
Chen, J., Abur, A., 2006. Placement of PMUs to enable bad data detection in state estimation. IEEE Trans. Power Syst. 21 (4), 1608–1615.
Chen, J., Thorp, J.S., Dobson, I., 2005. Cascading dynamics and mitigation assessment in power system disturbances via a hidden failure model. Int. J. Electr. Power Energy Syst. 27 (4), 318–326.
Chen, T.M., Sanchez-Aarnoutse, J.C., Buford, J., 2011. Petri net modeling of cyber-physical attacks on smart grid. IEEE Transactions on Smart Grid 2 (4), 741–749.
Chen, W., Zhou, K., Yang, S., Wu, C., 2017. Data quality of electricity consumption data in a smart grid environment. Renew. Sustain. Energy Rev. 75, 98–105.
Cheng, S., Malik, O., Hope, G., 1988. An expert system for voltage and reactive power control of a power system. IEEE Trans. Power Syst. 3 (4), 1449–1455.
Chiang, H.-D., Liu, C.-W., Varaiya, P.P., Wu, F.F., Lauby, M.G., 1993. Chaos in a simple power system. IEEE Trans. Power Syst. 8 (4), 1407–1417.
Ciavarella, S., Joo, J.-Y., Silvestri, S., 2016. Managing contingencies in smart grids via the internet of things. IEEE Transactions on Smart Grid 7 (4), 2134–2141.
Clastres, C., 2011. Smart grids: another step towards competition, energy security and climate change objectives. Energy Pol. 39 (9), 5399–5408.
Cloosterman, M.B., Van de Wouw, N., Heemels, W., Nijmeijer, H., 2009. Stability of networked control systems with uncertain time-varying delays. IEEE Trans. Automat. Contr. 54 (7), 1575–1580.
Coelho, E.A.A., Cortizo, P.C., Garcia, P.F.D., 2002. Small-signal stability for parallel-connected inverters in stand-alone AC supply systems. IEEE Trans. Ind. Appl. 38 (2), 533–542.
Coffele, F., Dolan, M., Booth, C., Ault, G., Burt, G., 2012. Coordination of protection and active network management for smart distribution networks. In: Integration of Renewables into the Distribution Grid. CIRED 2012 Workshop, pp. 1–4.
Cohenpb, J.E., Charles, M.N., 1985. When will a large complex system be stable? J. Theor. Biol. 113, 153–156.
Conejo, A.J., Morales, J.M., Baringo, L., 2010. Real-time demand response model. IEEE Transactions on Smart Grid 1 (3), 236–242.
Constantinescu, E.M., Zavala, V.M., Rocklin, M., Lee, S., Anitescu, M., 2010. A computational framework for uncertainty quantification and stochastic optimization in unit commitment with wind power generation. IEEE Trans. Power Syst. 26 (1), 431–441.
Copetti, J., Lorenzo, E., Chenlo, F., 1993. A general battery model for PV system simulation. Prog. Photovoltaics Res. Appl. 1 (4), 283–292.
Dahal, O.P., Brahma, S.M., Cao, H., 2013. Comprehensive clustering of disturbance events recorded by phasor measurement units. IEEE Trans. Power Deliv. 29 (3), 1390–1397.
Dänekas, C., González, J.M., 2013. Requirements engineering for smart grids. In: Standardization in Smart Grids. Springer, pp. 15–37.
Das, B., Pal, B.C., 2006. Voltage control performance of AWS connected for grid operation. IEEE Trans. Energy Convers. 21 (2), 353–361.
Delille, G., François, B., Malarange, G., 2010. Dynamic frequency control support: a virtual inertia provided by distributed energy storage to isolated power systems. In: 2010 IEEE PES Innovative Smart Grid Technologies Conference Europe (ISGT Europe), pp. 1–8.
Demiroren, A., Zeynelgil, H., Sengor, N., 2001. The application of ANN technique to load-frequency control for three-area power system. In: 2001 IEEE Porto Power Tech Proceedings (Cat. No. 01EX502), p. 5.
Deng, R., Yang, Z., Chow, M.-Y., Chen, J., 2015. A survey on demand response in smart grids: mathematical models and approaches. IEEE Transactions on Industrial Informatics 11 (3), 570–582.
Dhulst, R., Fernandez, J.M., Rikos, E., Kolodziej, D., Heussen, K., Geibelk, D., Temiz, A., Caerts, C., 2015. Voltage and frequency control for future power systems: the ELECTRA IRP proposal. In: 2015 International Symposium on Smart Electric Distribution Systems and Technologies (EDST), pp. 245–250.
Divan, D., Johal, H., 2005. Distributed FACTS-A new concept for realizing grid power flow control. In: Power Electronics Specialists Conference, 2005. PESC'05. IEEE 36th, pp. 8–14.
Divya, K., Ostergaard, J., 2009. Battery energy storage technology for power systems—an overview. Elec. Power Syst. Res. 79 (4), 511–520.
Djukanovic, M., Babic, B., Sobajic, D.J., Pao, Y.-H., 1993. Unsupervised/supervised learning concept for 24-hour load forecasting. In: IEE Proceedings C (Generation, Transmission and Distribution), pp. 311–318.
Dobson, I., Chen, J., Thorp, J., Carreras, B.A., Newman, D.E., 2002. Examining criticality of blackouts in power system models with cascading events. In: Proceedings of the 35th Annual Hawaii International Conference on System Sciences, p. 10.
Dobson, I., Carreras, B.A., Newman, D.E., 2005. A loading-dependent model of probabilistic cascading failure. Probab. Eng. Inf. Sci. 19 (1), 15–32.
Dörfler, F., Chertkov, M., Bullo, F., 2013. Synchronization in complex oscillator networks and smart grids. Proc. Natl. Acad. Sci. Unit. States Am. 110 (6), 2005–2010.
Edwards, M., Rambani, A., Zhu, Y., Musavi, M., 2012. Design of hadoop-based framework for analytics of large synchrophasor datasets. Procedia Computer Science 12, 254–258.
Efthymiou, C., Kalogridis, G., 2010. Smart grid privacy via anonymization of smart metering data. In: 2010 First IEEE International Conference on Smart Grid Communications, pp. 238–243.

Eriksson, M., Armendariz, M., Vasilenko, O.O., Saleem, A., Nordström, L., 2014. Multiagent-based distribution automation solution for self-healing grids. IEEE Trans. Ind. Electron. 62 (4), 2620–2628.
Erkin, Z., Troncoso-Pastoriza, J.R., Lagendijk, R.L., Pérez-González, F., 2013. Privacy-preserving data aggregation in smart metering systems: an overview. IEEE Signal Process. Mag. 30 (2), 75–86.
Esmalifalak, M., Liu, L., Nguyen, N., Zheng, R., Han, Z., 2017. Detecting stealthy false data injection using machine learning in smart grid. IEEE Systems Journal 11, 1644–1652.
Estebsari, A., Barbierato, L., Bahmanyar, A., Bottaccioli, L., Macii, E., Patti, E., 2019. A SGAM-based test platform to develop a scheme for wide area measurement-free monitoring of smart grids under high PV penetration. Energies 12 (8), 1417.
Etherden, N., Vyatkin, V., Bollen, M.H., 2016. Virtual power plant for grid services using IEC 61850. IEEE Transactions on Industrial Informatics 12 (1), 437–447.
Faheem, M., Gungor, V., 2018. Energy efficient and QoS-aware routing protocol for wireless sensor network-based smart grid applications in the context of industry 4.0. Appl. Soft Comput. 68, 910–922.
Fang, B., Yin, X., Tan, Y., Li, C., Gao, Y., Cao, Y., Li, J., 2016. The contributions of cloud technologies to smart grid. Renew. Sustain. Energy Rev. 59, 1326–1331.
Farr, R.S., Harer, J.L., Fink, T.M., 2014. Easily repairable networks: reconnecting nodes after damage. Phys. Rev. Lett. 113 (13), 138701.
Faschang, M., Cejka, S., Stefan, M., Frischenschlager, A., Einfalt, A., Diwold, K., Andrén, F.P., Strasser, T., Kupzog, F., 2017. Provisioning, deployment, and operation of smart grid applications on substation level. Comput. Sci. Res. Dev. 32 (1–2), 117–130.
Forsyth, A., Mollov, S., 1998. Modelling and control of DC-DC converters. Power Eng. J. 12 (5), 229–236.
Galli, S., Scaglione, A., Wang, Z., 2011. For the grid and through the grid: the role of power line communications in the smart grid. Proc. IEEE 99 (6), 998–1027.
Garcia, F.D., Jacobs, B., 2010. Privacy-friendly energy-metering via homomorphic encryption. In: International Workshop on Security and Trust Management, pp. 226–238.
Gellings, C.W., Smith, W.M., 1989. Integrating demand-side management into utility planning. Proc. IEEE 77 (6), 908–918.
Gerbex, S., Cherkaoui, R., Germond, A.J., 2001. Optimal location of multi-type FACTS devices in a power system by means of genetic algorithms. IEEE Trans. Power Syst. 16 (3), 537–544.
Giani, A., Bitar, E., Garcia, M., McQueen, M., Khargonekar, P., Poolla, K., 2013. Smart grid data integrity attacks. IEEE Transactions on Smart Grid 4 (3), 1244–1253.
Golshannavaz, S., Afsharnia, S., Aminifar, F., 2014. Smart distribution grid: optimal day-ahead scheduling with reconfigurable topology. IEEE Transactions on Smart Grid 5 (5), 2402–2411.
Gottwalt, S., Ketter, W., Block, C., Collins, J., Weinhardt, C., 2011. Demand side management—a simulation of household behavior under variable prices. Energy Pol. 39 (12), 8163–8174.
Gounaris, A., Yfoulis, C., Sakellariou, R., Dikaiakos, M.D., 2008. A control theoretical approach to self-optimizing block transfer in web service grids. ACM Trans. Autonom. Adapt. Syst. 3 (2), 1–30.
Greenblatt, J.B., Succar, S., Denkenberger, D.C., Williams, R.H., Socolow, R.H., 2007. Baseload wind energy: modeling the competition between gas turbines and compressed air energy storage for supplemental generation. Energy Pol. 35 (3), 1474–1492.
Gribble, S.D., 2001. Robustness in complex systems. In: Proceedings Eighth Workshop on Hot Topics in Operating Systems, pp. 21–26.
Gronquist, J.F., Sethares, W.A., Alvarado, F.L., Lasseter, R.H., 1995. Power oscillation damping control strategies for FACTS devices using locally measurable quantities. IEEE Trans. Power Syst. 10 (3), 1598–1605.
Guan, Z., Si, G., 2017. Achieving privacy-preserving big data aggregation with fault tolerance in smart grid. Digital Communications and Networks 3 (4), 242–249.
Guha, D., Roy, P.K., Banerjee, S., 2016. Load frequency control of interconnected power system using grey wolf optimization. Swarm and Evolutionary Computation 27, 97–115.
Guillo-sansano, E., Syed, M., Dambrauskas, P., Chen, M., Burt, G., McArthur, S., Strasser, T., 2016. Transitioning from centralized to distributed control: using SGAM to support a collaborative development of web of cells architecture for real time control. In: CIRED Workshop 2016, pp. 1–4.
Guillo-Sansano, E., Syed, M.H., Roscoe, A.J., Burt, G., Stanovich, M., Schoder, K., 2016. Controller HIL testing of real-time distributed frequency control for future power systems. In: 2016 IEEE PES Innovative Smart Grid Technologies Conference Europe (ISGT-Europe), pp. 1–6.
Gungor, V.C., Lu, B., Hancke, G.P., 2010. Opportunities and challenges of wireless sensor networks in smart grid. IEEE Trans. Ind. Electron. 57 (10), 3557–3564.
Guo, T., Milanovic, J.V., 2015. Online identification of power system dynamic signature using PMU measurements and data mining. IEEE Trans. Power Syst. 31 (3), 1760–1768.
Guo, H., Zheng, C., Iu, H.H.-C., Fernando, T., 2017. A critical review of cascading failure analysis and modeling of power system. Renew. Sustain. Energy Rev. 80, 9–22.
Gupta, R.A., Chow, M.-Y., 2009. Networked control system: overview and research trends. IEEE Trans. Ind. Electron. 57 (7), 2527–2535.
Gustavsson, R., Hussain, S., Saleem, A., 2013. Ancillary services for smart grids—power quality markets. In: PowerTech (POWERTECH), 2013 IEEE Grenoble, pp. 1–6.
Gyuk, I., Kulkarni, P., Sayer, J., Boyes, J., Corey, G., Peek, G., 2005. The United States of storage [electric energy storage]. IEEE Power Energy Mag. 3 (2), 31–39.
Hadjipaschalis, I., Poullikkas, A., Efthimiou, V., 2009. Overview of current and future energy storage technologies for electric power applications. Renew. Sustain. Energy Rev. 13 (6–7), 1513–1522.
Hahn, A., Govindarasu, M., 2011. Cyber attack exposure evaluation framework for the smart grid. IEEE Transactions on Smart Grid 2 (4), 835–843.
Hahn, A., Ashok, A., Sridhar, S., Govindarasu, M., 2013. Cyber-physical security testbeds: architecture, application, and evaluation for smart grid. IEEE Transactions on Smart Grid 4 (2), 847–855.
Haida, T., Muto, S., 1994. Regression based peak load forecasting using a transformation technique. IEEE Trans. Power Syst. 9 (4), 1788–1794.
Henriksson, D., Cervin, A., Årzén, K.-E., 2003. TrueTime: real-time control system simulation with MATLAB/Simulink. In: Proceedings of the Nordic MATLAB Conference.
Hespanha, J.P., Naghshtabrizi, P., Xu, Y., 2007. A survey of recent results in networked control systems. Proc. IEEE 95 (1), 138–162.
Heussen, K., Uslar, M., Tornelli, C., 2015. A use case methodology to handle conflicting controller requirements for future power systems. In: 2015 International Symposium on Smart Electric Distribution Systems and Technologies (EDST), pp. 582–587.
Hill, C.A., Such, M.C., Chen, D., Gonzalez, J., Grady, W.M., 2012. Battery energy storage for enabling integration of distributed solar power generation. IEEE Transactions on Smart Grid 3 (2), 850–857.
Hink, R.C.B., Beaver, J.M., Buckner, M.A., Morris, T., Adhikari, U., Pan, S., 2014. Machine learning for power system disturbance and cyber-attack discrimination. In: Resilient Control Systems (ISRCS), 2014 7th International Symposium on, pp. 1–8.
Hirsch, P., 1994. Extended Transient-Midterm Stability Program (ETMSP), Ver. 3.1 User's Manual. EPRI. TR-102004-V2R1.
Hommelberg, M., Warmer, C., Kamphuis, I., Kok, J., Schaeffer, G., 2007. Distributed control concepts using multi-agent technology and automatic markets: an indispensable feature of smart power grids. In: 2007 IEEE Power Engineering Society General Meeting, pp. 1–7.
Hota, A.R., Juvvanapudi, M., Bajpai, P., 2014. Issues and solution approaches in PHEV integration to smart grid. Renew. Sustain. Energy Rev. 30, 217–229.
Hu, J., Morais, H., Sousa, T., Lind, M., 2016. Electric vehicle fleet management in smart grids: a review of services, optimization and control aspects. Renew. Sustain. Energy Rev. 56, 1207–1226.
Huang, A.Q., Crow, M.L., Heydt, G.T., Zheng, J.P., Dale, S.J., 2010. The future renewable electric energy delivery and management (FREEDM) system: the energy internet. Proc. IEEE 99 (1), 133–148.
Huang, Z., Du, P., Kosterev, D., Yang, S., 2013. Generator dynamic model validation and parameter calibration using phasor measurements at the point of connection. IEEE Trans. Power Syst. 28 (2), 1939–1949.
Huang, B., Bai, X., Zhou, Z., Cui, Q., Zhu, D., Hu, R., 2017. Energy informatics: fundamentals and standardization. ICT Express 3 (2), 76–80.
Hung, G.-K., Chang, C.-C., Chen, C.-L., 2003. Automatic phase-shift method for islanding detection of grid-connected photovoltaic inverters. IEEE Trans. Energy Convers. 18 (1), 169–173.
Hussain, S., Gustavsson, R., Saleem, A., Nordström, L., 2012. Service level agreement: coordination and monitoring of actors in smart grid. In: Innovative Smart Grid Technologies (ISGT Europe), 2012 3rd IEEE PES International Conference and Exhibition on, pp. 1–7.
Hussein, K., Muta, I., Hoshino, T., Osakada, M., 1995. Maximum photovoltaic power tracking: an algorithm for rapidly changing atmospheric conditions. IEE Proc. Generat. Transm. Distrib. 142 (1), 59–64.
IEEE Smart Grid Vision for Computing, 2013. Beyond. IEEE Standards, pp. 1–133.
Jaalam, N., Rahim, N., Bakar, A., Tan, C., Haidar, A.M., 2016. A comprehensive review of synchronization methods for grid-connected converters of renewable energy source. Renew. Sustain. Energy Rev. 59, 1471–1481.
Jaradat, M., Jarrah, M., Bousselham, A., Jararweh, Y., Al-Ayyoub, M., 2015. The internet of energy: smart sensor networks and big data management for smart grid. Procedia Computer Science 56, 592–597.
Järventausta, P., Repo, S., Rautiainen, A., Partanen, J., 2010. Smart grid power system control in distributed generation environment. Annu. Rev. Contr. 34 (2), 277–286.
Kammerstetter, M., Langer, L., Skopik, F., Kastner, W., 2014. Architecture-driven smart grid security management. In: Proceedings of the 2nd ACM Workshop on Information Hiding and Multimedia Security, pp. 153–158.
Kang, Q., Zhou, M., An, J., Wu, Q., 2012. Swarm intelligence approaches to optimal power flow problem with distributed generator failures in power networks. IEEE Trans. Autom. Sci. Eng. 10 (2), 343–353.
Kar, S., Samantaray, S., Zadeh, M.D., 2017. Data-mining model based intelligent differential microgrid protection scheme. IEEE Systems Journal 11 (2), 1161–1169.
Karlsson, D., Hill, D.J., 1994. Modelling and identification of nonlinear dynamic loads in power systems. IEEE Trans. Power Syst. 9 (1), 157–166.
Karnouskos, S., 2010. The cooperative internet of things enabled smart grid. In: Proceedings of the 14th IEEE International Symposium on Consumer Electronics (ISCE2010), June. pp.07–10.
Katayama, M., Yamazato, T., Okada, H., 2006. A mathematical model of noise in narrowband power line communication systems. IEEE J. Sel. Area. Commun. 24 (7), 1267–1276.
Katiraei, F., Iravani, M.R., Lehn, P.W., 2005. Micro-grid autonomous operation during and subsequent to islanding process. IEEE Trans. Power Deliv. 20 (1), 248–257.
Kelly, J., Knottenbelt, W., 2015. The UK-DALE dataset, domestic appliance-level

electricity demand and whole-house demand from five UK homes. Scientific Data 2 (1), 1–14.
Kezunovic, M., Guo, Y., 2000. Modeling and simulation of the power transformer faults and related protective relay behavior. IEEE Trans. Power Deliv. 15 (1), 44–50.
Khan, M., Iqbal, M., 2005. Dynamic modeling and simulation of a small wind-fuel cell hybrid energy system. Renew. Energy 30 (3), 421–439.
Khan, J., Bhuiyan, S.M., Murphy, G., Arline, M., 2015. Embedded-zerotree-wavelet-based data denoising and compression for smart grid. IEEE Trans. Ind. Appl. 51 (5), 4190–4200.
Khan, A.R., Mahmood, A., Safdar, A., Khan, Z.A., Khan, N.A., 2016. Load forecasting, dynamic pricing and DSM in smart grid: a review. Renew. Sustain. Energy Rev. 54, 1311–1322.
Khayyam, S., Ponci, F., Goikoetxea, J., Recagno, V., Bagliano, V., Monti, A., 2016. Railway energy management system: centralized-decentralized automation architecture. IEEE Transactions on Smart Grid 7 (2), 1164–1175.
Kirpes, B., Danner, P., Basmadjian, R., De Meer, H., Becker, C., 2019. E-mobility systems architecture: a model-based framework for managing complexity and interoperability. Energy Informatics 2 (1), 15.
Konishi, K., Sugitani, Y., Hara, N., 2015. Dynamics of dc bus networks and their stabilization by decentralized delayed feedback. Phys. Rev. 91 (1), 012911.
Korjenic, A., Bednar, T., 2011. Impact of lifestyle on the energy demand of a single family house. In: Building Simulation, pp. 89–95.
Korkali, M., Veneman, J.G., Tivnan, B.F., Bagrow, J.P., Hines, P.D., 2017. Reducing cascading failure risk by increasing infrastructure network interdependence. Sci. Rep. 7 (1), 1–13.
Kothari, D.P., Nagrath, I., 2011. Modern Power System Analysis. Tata McGraw-Hill Education.
Kottick, D., Blau, M., Edelstein, D., 1993. Battery energy storage for frequency regulation in an island power system. IEEE Trans. Energy Convers. 8 (3), 455–459.
Kraus, J., Stepán, P., Kukavcka, L., 2012. Optimal data compression techniques for smart grid and power quality trend data. In: 2012 IEEE 15th International Conference on Harmonics and Quality of Power, pp. 707–712.
Kumar, P., Kothari, D.P., 2005. Recent philosophies of automatic generation control strategies in power systems. IEEE Trans. Power Syst. 20 (1), 346–357.
Kundur, P., Balu, N.J., Lauby, M.G., 1994. Power System Stability and Control. McGraw-hill, New York.
Kwac, J., Flora, J., Rajagopal, R., 2014. Household energy consumption segmentation using hourly data. IEEE Transactions on Smart Grid 5 (1), 420–430.
Langer, L., Skopik, F., Smith, P., Kammerstetter, M., 2016. From old to new: assessing cybersecurity risks for an evolving smart grid. Comput. Secur. 62, 165–176.
Lave, M., Kleissl, J., Stein, J.S., 2012. A wavelet-based variability model (WVM) for solar PV power plants. IEEE Transactions on Sustainable Energy 4 (2), 501–509.
Laverty, D.M., Best, R.J., Morrow, D.J., 2015. Loss-of-mains protection system by application of phasor measurement unit technology with experimentally assessed threshold settings. IET Gener., Transm. Distrib. 9 (2), 146–153.
Le Fevre Kristensen, T., Olsen, R.L., Rasmussen, J.G., Schwefel, H.-P., 2018. Information access for event-driven smart grid controllers. Sustainable Energy, Grids and Networks 13, 78–92.
Lee, M.J., Kim, B.J., 2017. Spatial uniformity in the power-grid system. Phys. Rev. 95 (4), 042316.
Lee, D.-J., Wang, L., 2008. Small-signal stability analysis of an autonomous hybrid renewable energy power generation/energy storage system part I: time-domain simulations. IEEE Trans. Energy Convers. 23 (1), 311–320.
Lei, Y., Mullane, A., Lightbody, G., Yacamini, R., 2006. Modeling of the wind turbine with a doubly fed induction generator for grid integration studies. IEEE Trans. Energy Convers. 21 (1), 257–264.
Leonardi, A., Mathioudakis, K., Wiesmaier, A., Zeiger, F., 2014. Towards the smart grid: substation automation architecture and technologies. Advances in Electrical Engineering 2014.
Leszczyna, R., 2018. Cybersecurity and privacy in standards for smart grids-A comprehensive survey. Comput. Stand. Interfac. 56, 62–73.
Li, F., Luo, B., 2012. Preserving data integrity for smart grid data aggregation. In: 2012 IEEE Third International Conference on Smart Grid Communications (SmartGridComm), pp. 366–371.
Li, F., Luo, B., Liu, P., 2010. Secure information aggregation for smart grids using homomorphic encryption. In: Smart Grid Communications (SmartGridComm), 2010 First IEEE International Conference on, pp. 327–332.
Li, G., Weiss, G., Mueller, M., Townley, S., Belmont, M.R., 2012. Wave energy converter control by wave prediction and dynamic programming. Renew. Energy 48, 392–403.
Li, X., Hui, D., Lai, X., 2013. Battery energy storage station (BESS)-based smoothing control of photovoltaic (PV) and wind power generation fluctuations. IEEE Transactions on Sustainable Energy 4 (2), 464–473.
Li, W., Ferdowsi, M., Stevic, M., Monti, A., Ponci, F., 2014. Cosimulation for smart grid communications. IEEE Transactions on Industrial Informatics 10 (4), 2374–2384.
Lindquist, T., Bertling, L., Eriksson, R., 2008. Circuit breaker failure data and reliability modelling. IET Gener., Transm. Distrib. 2 (6), 813–820.
Liu, Y., Liu, Y., 2006. Aspects on power system islanding for preventing widespread blackout. In: Networking, Sensing and Control, 2006. ICNSC'06. Proceedings of the 2006 IEEE International Conference on, pp. 1090–1095.
Liu, C.-C., Tomsovic, K., 1986. An expert system assisting decision-making of reactive power/voltage control. IEEE Trans. Power Syst. 1 (3), 195–201.
Liu, G., Mu, J., Rees, D., Chai, S., 2006. Design and stability analysis of networked control systems with random communication time delay using the modified MPC. Int. J. Contr. 79 (4), 288–297.
Liu, H., Chen, X., Yu, K., Hou, Y., 2012. The control and analysis of self-healing urban power grid. IEEE Transactions on Smart Grid 3 (3), 1119–1129.
Liu, N., Yu, X., Wang, C., Li, C., Ma, L., Lei, J., 2017. Energy-sharing model with price-based demand response for microgrids of peer-to-peer prosumers. IEEE Trans. Power Syst. 32 (5), 3569–3583.
Logenthiran, T., Srinivasan, D., Shun, T.Z., 2012. Demand side management in smart grid using heuristic optimization. IEEE Transactions on Smart Grid 3 (3), 1244–1252.
Long, C., Wu, J., Zhang, C., Thomas, L., Cheng, M., Jenkins, N., 2017. Peer-to-peer energy trading in a community microgrid. In: 2017 IEEE Power & Energy Society General Meeting, pp. 1–5.
López, G., Moura, P., Moreno, J.I., Camacho, J.M., 2014. Multi-faceted assessment of a wireless communications infrastructure for the green neighborhoods of the smart grid. Energies 7 (5), 3453–3483.
López, G., Custodio, V., Moreno, J.I., Sikora, M., Moura, P., Fernández, N., 2015. Modeling smart grid neighborhoods with the ENERsip ontology. Comput. Ind. 70, 168–182.
Lorca, A., Sun, X.A., 2014. Adaptive robust optimization with dynamic uncertainty sets for multi-period economic dispatch under significant wind. IEEE Trans. Power Syst. 30 (4), 1702–1713.
Lu, C.-F., Liu, C.-C., Wu, C.-J., 1995. Dynamic modelling of battery energy storage system and application to power system stability. IEE Proc. Generat. Transm. Distrib. 142 (4), 429–435.
Lu, R., Liang, X., Li, X., Lin, X., Shen, X., 2012. Eppa: an efficient and privacy-preserving aggregation scheme for secure smart grid communications. IEEE Trans. Parallel Distr. Syst. 23 (9), 1621–1631.
Luo, X., Wang, J., Dooner, M., Clarke, J., 2015. Overview of current development in electrical energy storage technologies and the application potential in power system operation. Appl. Energy 137, 511–536.
Ma, O., Alkadi, N., Cappers, P., Denholm, P., Dudley, J., Goli, S., Hummon, M., Kiliccote, S., MacDonald, J., Matson, N., others, 2013. Demand response for ancillary services. IEEE Transactions on Smart Grid 4 (4), 1988–1995.
Ma, K., Yao, T., Yang, J., Guan, X., 2016. Residential power scheduling for demand response in smart grid. Int. J. Electr. Power Energy Syst. 78, 320–325.
Ma, Z., Hudic, A., Shaaban, A., Plosz, S., 2017. Security viewpoint in a reference architecture model for cyber-physical production systems. In: Security and Privacy Workshops (EuroS&PW), 2017 IEEE European Symposium on, pp. 153–159.
Mackiewicz, R.E., 2006. Overview of IEC 61850 and benefits. In: 2006 IEEE Power Engineering Society General Meeting, p. 8.
Madureira, A., Lopes, J.P., 2012. Ancillary services market framework for voltage control in distribution networks with microgrids. Elec. Power Syst. Res. 86, 1–7.
Maharjan, S., Zhu, Q., Zhang, Y., Gjessing, S., Basar, T., 2013. Dependable demand response management in the smart grid: a Stackelberg game approach. IEEE Transactions on Smart Grid 4 (1), 120–132.
Mahmud, K., Sahoo, A.K., Fernandez, E., Sanjeevikumar, P., Holm-Nielsen, J.B., 2020. Computational tools for modeling and analysis of power generation and transmission systems of the smart grid. IEEE Systems Journal 14 (3), 3641–3652.
Makarov, Y.V., Etingov, P.V., Ma, J., Huang, Z., Subbarao, K., 2011. Incorporating uncertainty of wind power generation forecast into power system operation, dispatch, and unit commitment procedures. IEEE Transactions on Sustainable Energy 2 (4), 433–442.
Malinowski, M., Kazmierkowski, M.P., Hansen, S., Blaabjerg, F., Marques, G., 2001. Virtual-flux-based direct power control of three-phase PWM rectifiers. IEEE Trans. Ind. Appl. 37 (4), 1019–1027.
Malinowski, M., Jasinski, M., Kazmierkowski, M.P., 2004. Simple direct power control of three-phase PWM rectifier using space-vector modulation (DPC-SVM). IEEE Trans. Ind. Electron. 51 (2), 447–454.
Mármol, F.G., Sorge, C., Ugus, O., Pérez, G.M., 2012. Do not snoop my habits: preserving privacy in the smart grid. IEEE Commun. Mag. 50 (5), 166–172.
Martini, L., Brunner, H., Rodriguez, E., Caerts, C., Strasser, T.I., Burt, G.M., 2017. Grid of the future and the need for a decentralised control architecture: the web-of-cells concept. CIRED-Open Access Proceedings Journal 2017 (1), 1162–1166.
Matallanas, E., Castillo-Cagigal, M., Gutiérrez, A., Monasterio-Huelin, F., Caamaño-Martin, E., Masa, D., Jiménez-Leube, J., 2012. Neural network controller for active demand-side management with PV energy in the residential sector. Appl. Energy 91 (1), 90–97.
McGranaghan, M., Houseman, D., Schmitt, L., Cleveland, F., Lambert, E., 2016. Enabling the integrated grid: leveraging data to integrate distributed resources and customers. IEEE Power Energy Mag. 14 (1), 83–93.
Meng, H., Guan, Y.L., Chen, S., 2005. Modeling and analysis of noise effects on broadband power-line communications. IEEE Trans. Power Deliv. 20 (2), 630–637.
Mercier, P., Cherkaoui, R., Oudalov, A., 2009. Optimizing a battery energy storage system for frequency control application in an isolated power system. IEEE Trans. Power Syst. 24 (3), 1469–1477.
Metke, A.R., Ekl, R.L., 2010. Security technology for smart grid networks. IEEE Transactions on Smart Grid 1 (1), 99–107.
Mets, K., Verschueren, T., Develder, C., Vandoorn, T.L., Vandevelde, L., 2011. Integrated simulation of power and communication networks for smart grid applications. In: Computer Aided Modeling and Design of Communication Links

and Networks (CAMAD), 2011 IEEE 16th International Workshop on, pp. 61–65.
Milano, F., 2005. An open source power system analysis toolbox. IEEE Trans. Power Syst. 20 (3), 1199–1206.
Mitchell, M.A., Lopes, J.P., Fidalgo, J., McCalley, J.D., 2000. Using a neural network to predict the dynamic frequency response of a power system to an under-frequency load shedding scenario. In: Power Engineering Society Summer Meeting, 2000. IEEE, pp. 346–351.
Mohsenian-Rad, A.-H., Wong, V.W., Jatskevich, J., Schober, R., Leon-Garcia, A., 2010. Autonomous demand-side management based on game-theoretic energy consumption scheduling for the future smart grid. IEEE Transactions on Smart Grid 1 (3), 320–331.
Molina, E., Jacob, E., Matias, J., Moreira, N., Astarloa, A., 2015. Using software defined networking to manage and control IEC 61850-based systems. Comput. Electr. Eng. 43, 142–154.
Moness, M., Moustafa, A.M., 2015. A survey of cyber-physical advances and challenges of wind energy conversion systems: prospects for internet of energy. IEEE Internet of Things Journal 3 (2), 134–145.
Montes, M., Abánades, A., Martinez-Val, J., Valdés, M., 2009. Solar multiple optimization for a solar-only thermal power plant, using oil as heat transfer fluid in the parabolic trough collectors. Sol. Energy 83 (12), 2165–2176.
Montestruque, L.A., Antsaklis, P., 2004. Stability of model-based networked control systems with time-varying transmission times. IEEE Trans. Automat. Contr. 49 (9), 1562–1572.
Morstyn, T., Farrell, N., Darby, S.J., McCulloch, M.D., 2018. Using peer-to-peer energy-trading platforms to incentivize prosumers to form federated power plants. Nature Energy 3 (2), 94–101.
Moslehi, K., Kumar, R., 2010. Smart grid-a reliability perspective. In: 2010 Innovative Smart Grid Technologies (ISGT), pp. 1–8.
Moura, P.S., De Almeida, A.T., 2010. The role of demand-side management in the grid integration of wind power. Appl. Energy 87 (8), 2581–2588.
Moya, O.E., 2005. A spinning reserve, load shedding, and economic dispatch solution by Bender's decomposition. IEEE Trans. Power Syst. 20 (1), 384–388.
Mureddu, M., Caldarelli, G., Damiano, A., Scala, A., Meyer-Ortmanns, H., 2016. Islanding the power grid on the transmission level: less connections for more security. Sci. Rep. 6, 34797.
Nassar, M., Lin, J., Mortazavi, Y., Dabak, A., Kim, I.H., Evans, B.L., 2012. Local utility power line communications in the 3-500 kHz band: channel impairments, noise, and standards. IEEE Signal Process. Mag. 29 (5), 116–127.
Neureiter, C., Engel, D., Trefke, J., Santodomingo, R., Rohjans, S., Uslar, M., 2014. Towards consistent smart grid architecture tool support: from use cases to visualization. In: Innovative Smart Grid Technologies Conference Europe (ISGT-Europe), 2014 IEEE PES, pp. 1–6.
Neureiter, C., Eibl, G., Engel, D., Schlegel, S., Uslar, M., 2016. A concept for engineering smart grid security requirements based on SGAM models. Comput. Sci. Res. Dev. 31 (1–2), 65–71.
Nguyen, H.K., Song, J.B., Han, Z., 2012. Demand side management to reduce peak-to-average ratio using game theory in smart grid. In: 2012 Proceedings IEEE INFOCOM Workshops, pp. 91–96.
Nguyen, P.H., Kling, W.L., Ribeiro, P.F., 2013. A game theory strategy to integrate distributed agent-based functions in smart grids. IEEE Transactions on Smart Grid 4 (1), 568–576.
Ni, H., Heydt, G.T., Mili, L., 2002. Power system stability agents using robust wide area control. IEEE Trans. Power Syst. 17 (4), 1123–1131.
Nieße, A., Lehnhoff, S., Tröschel, M., Uslar, M., Wissing, C., Appelrath, H.-J., Sonnenschein, M., 2012. Market-based self-organized provision of active power and ancillary services: an agent-based approach for smart distribution grids. In: 2012 Complexity in Engineering (COMPENG). Proceedings, pp. 1–5.
Nieße, A., Tröschel, M., Sonnenschein, M., 2014. Designing dependable and sustainable Smart Grids-How to apply Algorithm Engineering to distributed control in power systems. Environ. Model. Software 56, 37–51.
NIST Framework 2.0, 2010. Roadmap for smart grid interoperability standards [online] *National Institute of Standards and Technology*. Available at: https://www.nist.gov/system/files/documents/smartgrid/NIST_Framework_Release_2-0_corr.pdf.
Ohnishi, T., 1991. Three phase PWM converter/inverter by means of instantaneous active and reactive power control. In: Proc. IEEE IECON., pp. 819–824.
Olivares, D.E., Mehrizi-Sani, A., Etemadi, A.H., Cañizares, C.A., Iravani, R., Kazerani, M., Hajimiragha, A.H., Gomis-Bellmunt, O., Saeedifard, M., Palma-Behnke, R., others, 2014. Trends in microgrid control. IEEE Transactions on Smart Grid 5 (4), 1905–1919.
Ortega-Vazquez, M.A., Kirschen, D.S., 2008. Estimating the spinning reserve requirements in systems with significant wind power generation penetration. IEEE Trans. Power Syst. 24 (1), 114–124.
Palensky, P., Dietrich, D., 2011. Demand side management: demand response, intelligent energy systems, and smart loads. IEEE Transactions on Industrial Informatics 7 (3), 381–388.
Pan, C.-T., Liaw, C.-M., 1989. An adaptive controller for power system load-frequency control. IEEE Trans. Power Syst. 4 (1), 122–128.
Panda, D.K., Das, S., 2020. Economic operational analytics for energy storage placement at different grid locations and contingency scenarios with stochastic wind profiles. Renew. Sustain. Energy Rev. 110474.
Panda, S., Yegireddy, N.K., 2013. Automatic generation control of multi-area power system using multi-objective non-dominated sorting genetic algorithm-II. Int. J. Electr. Power Energy Syst. 53, 54–63.
Panda, D.K., Das, S., Townley, S., 2020. Toward a more renewable energy-based LFC under random packet transmissions and delays with stochastic generation and demand. IEEE Trans. Autom. Sci. Eng. https://doi.org/10.1109/TASE.2020.3042570.
Papalexopoulos, A.D., Hesterberg, T.C., 1990. A regression-based approach to short-term system load forecasting. IEEE Trans. Power Syst. 5 (4), 1535–1547.
Park, D.C., El-Sharkawi, M., Marks, R., Atlas, L., Damborg, M., 1991. Electric load forecasting using an artificial neural network. IEEE Trans. Power Syst. 6 (2), 442–449.
Penalba, M., Giorgi, G., Ringwood, J.V., 2017. Mathematical modelling of wave energy converters: a review of nonlinear approaches. Renew. Sustain. Energy Rev. 78, 1188–1207.
Po, H.F., Yeung, C.H., Zeng, A., Wong, K.M., 2017. Evolving power grids with self-organized intermittent strain releases: an analogy with sandpile models and earthquakes. Phys. Rev. 96 (5), 052312.
Poon, S.-H., Granger, C.W., 2003. Forecasting volatility in financial markets: a review. J. Econ. Lit. 41 (2), 478–539.
Powell, K.M., Edgar, T.F., 2012. Modeling and control of a solar thermal power plant with thermal energy storage. Chem. Eng. Sci. 71, 138–145.
Prasad, G., Swidenbank, E., Hogg, B., 1998. A local model networks based multivariable long-range predictive control strategy for thermal power plants. Automatica 34 (10), 1185–1204.
Prasad, G., Irwin, G., Swidenbank, E., Hogg, B., 2000. Plant-wide predictive control for a thermal power plant based on a physical plant model. IEE Proc. Contr. Theor. Appl. 147 (5), 523–537.
Pujol, J.M., Sangüesa, R., Delgado, J., 2002. Extracting reputation in multi agent systems by means of social network topology. In: Proceedings of the First International Joint Conference on Autonomous Agents and Multiagent Systems, vol. 1, pp. 467–474.
Qi, H., Zhang, W., Tolbert, L.M., 2005. A resilient real-time agent-based system for a reconfigurable power grid. In: Proceedings of the 13th International Conference on, Intelligent Systems Application to Power Systems, pp. 43–48.
Qi, H., Wang, X., Tolbert, L.M., Li, F., Peng, F.Z., Ning, P., Amin, M., 2011. A resilient real-time system design for a secure and reconfigurable power grid. IEEE Transactions on Smart Grid 2 (4), 770–781.
Qian, L.P., Zhang, Y.J.A., Huang, J., Wu, Y., 2013. Demand response management via real-time electricity price control in smart grids. IEEE J. Sel. Area. Commun. 31 (7), 1268–1280.
Qiao, W., Harley, R.G., Venayagamoorthy, G.K., 2009. Coordinated reactive power control of a large wind farm and a STATCOM using heuristic dynamic programming. IEEE Trans. Energy Convers. 24 (2), 493–503.
Rao, P., Crow, M., Yang, Z., 2000. STATCOM control for power system voltage control applications. IEEE Trans. Power Deliv. 15 (4), 1311–1317.
Räsänen, T., Kolehmainen, M., 2009. Feature-based clustering for electricity use time series data. In: International Conference on Adaptive and Natural Computing Algorithms, pp. 401–412.
Räsänen, T., Voukantsis, D., Niska, H., Karatzas, K., Kolehmainen, M., 2010. Data-based method for creating electricity use load profiles using large amount of customer-specific hourly measured electricity use data. Appl. Energy 87 (11), 3538–3545.
Rerkpreedapong, D., Hasanovic, A., Feliachi, A., 2003. Robust load frequency control using genetic algorithms and linear matrix inequalities. Power Systems, IEEE Transactions on 18 (2), 855–861.
Ribeiro, P.F., Johnson, B.K., Crow, M.L., Arsoy, A., Liu, Y., 2001. Energy storage systems for advanced power applications. Proc. IEEE 89 (12), 1744–1756.
Roberts, B.P., Sandberg, C., 2011. The role of energy storage in development of smart grids. Proc. IEEE 99 (6), 1139–1144.
Roche, R., Natarajan, S., Bhattacharyya, A., Suryanarayanan, S., 2012. A framework for co-simulation of AI tools with power systems analysis software. In: Database and Expert Systems Applications (DEXA), 2012 23rd International Workshop on, pp. 350–354.
Rodriguez, C.T., De La Fuente, D.V., Garcerá, G., Figueres, E., Moreno, J.A.G., 2011. Reconfigurable control scheme for a PV microinverter working in both grid-connected and island modes. IEEE Trans. Ind. Electron. 60 (4), 1582–1595.
Rohden, M., Sorge, A., Timme, M., Witthaut, D., 2012. Self-organized synchronization in decentralized power grids. Phys. Rev. Lett. 109 (6), 064101.
Roscoe, A.J., Burt, G.M., McDonald, J., 2009. Frequency and fundamental signal measurement algorithms for distributed control and protection applications. IET Gener., Transm. Distrib. 3 (5), 485–495.
Roscoe, A.J., Bright, C., Galloway, S.J., Burt, G.M., 2011. Increasing security of supply by the use of a local power controller during large system disturbances. In: Innovative Smart Grid Technologies (ISGT Europe), 2011 2nd IEEE PES International Conference and Exhibition on, pp. 1–7.
Roscoe, A.J., Burt, G.M., Bright, C.G., 2014. Avoiding the non-detection zone of passive loss-of-mains (islanding) relays for synchronous generation by using low bandwidth control loops and controlled reactive power mismatches. IEEE Transactions on Smart Grid 5 (2), 602–611.
Rottondi, C., Verticale, G., Krauss, C., 2013. Distributed privacy-preserving aggregation of metering data in smart grids. IEEE J. Sel. Area. Commun. 31 (7), 1342–1354.
Ruland, K.C., Sassmannshausen, J., Waedt, K., Zivic, N., 2017. Smart grid security-an overview of standards and guidelines. E I Elektrotechnik Inf. 134 (1), 19–25.
Sabater, J., Sierra, C., 2002. Reputation and social network analysis in multi-agent systems. In: Proceedings of the First International Joint Conference on Autonomous Agents and Multiagent Systems, vol. 1, pp. 475–482.
Saber, A.Y., Venayagamoorthy, G.K., 2011. Resource scheduling under uncertainty in

a smart grid with renewables and plug-in vehicles. IEEE Systems Journal 6 (1), 103–109.
Sadeghzadeh, S., Ehsan, M., Said, N.H., Feuillet, R., 1998. Improvement of transient stability limit in power system transmission lines using fuzzy control of FACTS devices. IEEE Trans. Power Syst. 13 (3), 917–922.
Sakakibara, S., Flynn, B.B., Schroeder, R.G., Morris, W.T., 1997. The impact of just-in-time manufacturing and its infrastructure on manufacturing performance. Manag. Sci. 43 (9), 1246–1257.
Salinas, S., Li, M., Li, P., 2012. Multi-objective optimal energy consumption scheduling in smart grids. IEEE Transactions on Smart Grid 4 (1), 341–348.
Samadi, P., Mohsenian-Rad, H., Schober, R., Wong, V.W., 2012. Advanced demand side management for the future smart grid using mechanism design. IEEE Transactions on Smart Grid 3 (3), 1170–1180.
Samineni, S., Johnson, B.K., Hess, H.L., Law, J.D., 2006. Modeling and analysis of a flywheel energy storage system for voltage sag correction. IEEE Trans. Ind. Appl. 42 (1), 42–52.
Santodomingo, R., Uslar, M., Goring, A., Gottschalk, M., Nordstrom, L., Saleem, A., Chenine, M., 2014. SGAM-based methodology to analyse Smart Grid solutions in DISCERN European research project. In: Energy Conference (ENERGYCON), 2014 IEEE International, pp. 751–758.
Santodomingo, R., Uslar, M., Gottschlak, M., Goering, A., Nordström, L., Valdenmaiier, G., 2016. The DISCERN tool support for knowledge sharing in large Smart Grid projects. In: CIRED Workshop 2016, pp. 1–4.
Schäfer, B., Beck, C., Aihara, K., Witthaut, D., Timme, M., 2018. Non-Gaussian power grid frequency fluctuations characterized by Lévy-stable laws and superstatistics. Nature Energy 3 (2), 119–126.
Schintke, F., Schutt, T., Reinefeld, A., 2003. A framework for self-optimizing Grids using P2P components. In: 14th International Workshop on Database and Expert Systems Applications, 2003. Proceedings, pp. 689–693.
Schuh, G., Fluhr, J., Birkmeier, M., Sund, M., 2013. Information system architecture for the interaction of electric vehicles with the power grid. In: Networking, Sensing and Control (ICNSC), 2013 10th IEEE International Conference on, pp. 821–825.
Sedghi, M., Ahmadian, A., Aliakbar-Golkar, M., 2015. Optimal storage planning in active distribution network considering uncertainty of wind power distributed generation. IEEE Trans. Power Syst. 31 (1), 304–316.
Sexauer, J., Javanbakht, P., Mohagheghi, S., 2013. Phasor measurement units for the distribution grid: necessity and benefits. In: 2013 IEEE PES Innovative Smart Grid Technologies Conference (ISGT), pp. 1–6.
Shi, L., Crow, M., 2008. Comparison of ultracapacitor electric circuit models. In: Power and Energy Society General Meeting-Conversion and Delivery of Electrical Energy in the 21st Century, 2008 IEEE, pp. 1–6.
Simard, G., 2013. IEEE Grid Vision 2050. IEEE Standards, pp. 1–93.
Slootweg, J., De Haan, S., Polinder, H., Kling, W., 2003. General model for representing variable speed wind turbines in power system dynamics simulations. IEEE Trans. Power Syst. 18 (1), 144–151.
Soliman, H.M., Leon-Garcia, A., 2014. Game-theoretic demand-side management with storage devices for the future smart grid. IEEE Transactions on Smart Grid 5 (3), 1475–1485.
Soni, N., Doolla, S., Chandorkar, M.C., 2013. Improvement of transient response in microgrids using virtual inertia. IEEE Trans. Power Deliv. 28 (3), 1830–1838.
Spanò, E., Niccolini, L., Di Pascoli, S., Iannacconeluca, G., 2015. Last-meter smart grid embedded in an Internet-of-Things platform. IEEE Transactions on Smart Grid 6 (1), 468–476.
Sridhar, S., Hahn, A., Govindarasu, M., 2012. Cyber-physical system security for the electric power grid. Proc. IEEE 100 (1), 210–224.
Srivastava, A., Morris, T., Ernster, T., Vellaithurai, C., Pan, S., Adhikari, U., 2013. Modeling cyber-physical vulnerability of the smart grid with incomplete information. IEEE Transactions on Smart Grid 4 (1), 235–244.
Stagg, G.W., El-Abiad, A.H., 1968. Computer Methods in Power System Analysis. McGraw-Hill.
Su, W., Wang, J., Zhang, K., Huang, A.Q., 2014. Model predictive control-based power dispatch for distribution system considering plug-in electric vehicle uncertainty. Elec. Power Syst. Res. 106, 29–35.
Sugimori, Y., Kusunoki, K., Cho, F., Uchikawa, S., 1977. Toyota production system and kanban system materialization of just-in-time and respect-for-human system. Int. J. Prod. Res. 15 (6), 553–564.
Syed, M.H., Guillo-Sansano, E., Blair, S.M., Burt, G.M., Brunner, H., Gehrke, O., Rodriguez-Seco, J.E., others, 2017. Laboratory infrastructure driven key performance indicator development using the smart grid architecture model. CIRED-Open Access Proceedings Journal (1), 1866–1870, 2017.
Szekeres, A., Snekkenes, E., 2020. Representing decision-makers in SGAM-H: the smart grid architecture model extended with the human layer. In: International Workshop on Graphical Models for Security, pp. 87–110.
Szulecki, K., Ancygier, A., Szwed, D., 2015. Energy democratization? Societal aspects of de-carbonization in the German and Polish energy sectors. In: Societal Aspects of De-carbonization in the German and Polish Energy Sectors (March 9, 2015).
Talaq, J., Al-Basri, F., 1999. Adaptive fuzzy gain scheduling for load frequency control. Power Systems, IEEE Transactions on 14 (1), 145–150.
Tariq, M.U., Swenson, B.P., Narasimhan, A.P., Grijalva, S., Riley, G.F., Wolf, M., 2014. Cyber-physical co-simulation of smart grid applications using ns-3. In: Proceedings of the 2014 Workshop on Ns-3, p. 8.
Taylor, C.W., 1992. Concepts of undervoltage load shedding for voltage stability. IEEE Trans. Power Deliv. 7 (2), 480–488.
Tchuisseu, E.T., Gomila, D., Brunner, D., Colet, P., 2017. Effects of dynamic-demand-control appliances on the power grid frequency. Phys. Rev. 96 (2), 022302.
Teleke, S., Baran, M.E., Huang, A.Q., Bhattacharya, S., Anderson, L., 2009. Control strategies for battery energy storage for wind farm dispatching. IEEE Trans. Energy Convers. 24 (3), 725–732.
Terzija, V.V., 2006. Adaptive under frequency load shedding based on the magnitude of the disturbance estimation. IEEE Trans. Power Syst. 21 (3), 1260–1266.
Terzija, V., Valverde, G., Cai, D., Regulski, P., Madani, V., Fitch, J., Skok, S., Begovic, M.M., Phadke, A., 2011. Wide-area monitoring, protection, and control of future electric power networks. Proc. IEEE 99 (1), 80–93.
Thompson, G., Bazilian, M., 2014. Democratization, energy poverty, and the pursuit of symmetry. Global Policy 5 (1), 127–131.
Tielens, P., Van Hertem, D., 2016. The relevance of inertia in power systems. Renew. Sustain. Energy Rev. 55, 999–1009.
Timbus, A., Liserre, M., Teodorescu, R., Rodriguez, P., Blaabjerg, F., 2009. Evaluation of current controllers for distributed power generation systems. IEEE Trans. Power Electron. 24 (3), 654–664.
Timbus, A., Oudalov, A., Ho, C.N., 2010. Islanding detection in smart grids. In: Energy Conversion Congress and Exposition (ECCE), 2010 IEEE, pp. 3631–3637.
Tinney, W.F., Hart, C.E., 1967. Power flow solution by Newton's method. IEEE Trans. Power Apparatus Syst. (11), 1449–1460.
Tipsuwan, Y., Chow, M.-Y., 2003. Control methodologies in networked control systems. Contr. Eng. Pract. 11 (10), 1099–1111.
Tong, X., Kang, C., Xia, Q., 2016. Smart metering load data compression based on load feature identification. IEEE Transactions on Smart Grid 7 (5), 2414–2422.
Torriti, J., 2012. Price-based demand side management: assessing the impacts of time-of-use tariffs on residential electricity demand and peak shifting in Northern Italy. Energy 44 (1), 576–583.
Trefke, J., Dänekas, C., Rohjans, S., Vázquez, J.M.G., 2012. Adaptive architecture development for Smart Grids based on integrated building blocks. In: Innovative Smart Grid Technologies (ISGT Europe), 2012 3rd IEEE PES International Conference and Exhibition on, pp. 1–8.
Trefke, J., Rohjans, S., Uslar, M., Lehnhoff, S., Nordstrom, L., Saleem, A., 2013. Smart grid architecture model use case management in a large European smart grid project. In: Innovative Smart Grid Technologies Europe (ISGT EUROPE), 2013 4th IEEE/PES, pp. 1–5.
Uslar, M., Rosinger, C., Schlegel, S., 2014. Security by design for the smart grid: combining the SGAM and NISTIR 7628. In: Computer Software and Applications Conference Workshops (COMPSACW), 2014 IEEE 38th International, pp. 110–115.
Uzunoglu, M., Alam, M., 2006. Dynamic modeling, design, and simulation of a combined PEM fuel cell and ultracapacitor system for stand-alone residential applications. IEEE Trans. Energy Convers. 21 (3), 767–775.
Van Amelsvoort, M.A., 2016. SG-rating-Putting values on smart grid architectures. Inf. Technol. 58 (1), 29–36.
Vandael, S., Claessens, B., Hommelberg, M., Holvoet, T., Deconinck, G., 2012. A scalable three-step approach for demand side management of plug-in hybrid vehicles. IEEE Transactions on Smart Grid 4 (2), 720–728.
Vardakas, J.S., Zorba, N., Verikoukis, C.V., 2014. A survey on demand response programs in smart grids: pricing methods and optimization algorithms. IEEE Communications Surveys & Tutorials 17 (1), 152–178.
Vasquez, J.C., Guerrero, J.M., Luna, A., Rodriguez, P., Teodorescu, R., 2009. Adaptive droop control applied to voltage-source inverters operating in grid-connected and islanded modes. IEEE Trans. Ind. Electron. 56 (10), 4088–4096.
Venkatesan, N., Solanki, J., Solanki, S.K., 2012. Residential demand response model and impact on voltage profile and losses of an electric distribution network. Appl. Energy 96, 84–91.
Venturi, A., Dolan, M.J., Clarkson, P., Wright, P., Forbes, A., Yang, X.-S., Roscoe, A.J., Ault, G.W. and Burt, G.M., Evaluating the robustness of an active network management function in an operational environment. Electricity Distribution (CIRED 2013), 22nd International Conference and Exhibition on, pp.1–4.
Viswanath, S.K., Yuen, C., Tushar, W., Li, W.-T., Wen, C.-K., Hu, K., Chen, C., Liu, X., 2016. System design of the internet of things for residential smart grid. IEEE Wireless Communications 23 (5), 90–98.
Von Dollen, D., 2009. Report to NIST on the Smart Grid Interoperability Standards Roadmap. Electric Power Research Institute (EPRI) and National Institute of Standards and Technology [online] Available at: https://www.energy.gov/sites/prod/files/oeprod/DocumentsandMedia/Report_to_NIST_August10_2.pdf.
Vyas, S., Kumar, R., Kavasseri, R., 2017. Data analytics and computational methods for anti-islanding of renewable energy based Distributed Generators in power grids. Renew. Sustain. Energy Rev. 69, 493–502.
Vyatkin, V., 2011. IEC 61499 as enabler of distributed and intelligent automation: state-of-the-art review. IEEE Transactions on Industrial Informatics 7 (4), 768–781.
Walsh, G.C., Ye, H., Bushnell, L.G., 2002. Stability analysis of networked control systems. IEEE Trans. Contr. Syst. Technol. 10 (3), 438–446.
Wang, W., Lu, Z., 2013. Cyber security in the smart grid: survey and challenges. Comput. Network. 57 (5), 1344–1371.
Wang, Y., Wu, C., 2012. Forecasting energy market volatility using GARCH models: can multivariate models beat univariate models? Energy Econ. 34 (6), 2167–2181.
Wang, F., Duarte, J., Hendrix, M., 2010. Design and analysis of active power control strategies for distributed generation inverters under unbalanced grid faults. IET Gener., Transm. Distrib. 4 (8), 905–916.
Wang, W., Beddard, A., Barnes, M., Marjanovic, O., 2014. Analysis of active power

control for VSC-HVDC. IEEE Trans. Power Deliv. 29 (4), 1978–1988.
Wang, Z., Chen, B., Wang, J., Chen, C., 2015. Networked microgrids for self-healing power systems. IEEE Transactions on Smart Grid 7 (1), 310–319.
Wang, C., Grebogi, C., Baptista, M.S., 2016. Control and prediction for blackouts caused by frequency collapse in smart grids. Chaos: An Interdisciplinary Journal of Nonlinear Science 26 (9), 093119.
Wen, J., Wu, Q., Turner, D., Cheng, S., Fitch, J., 2004. Optimal coordinated voltage control for power system voltage stability. IEEE Trans. Power Syst. 19 (2), 1115–1122.
Wen, L., Zhou, K., Yang, S., Li, L., 2018. Compression of smart meter big data: a survey. Renew. Sustain. Energy Rev. 91, 59–69.
Willner, A., Gowtham, V., 2020. Toward a reference architecture model for industrial edge computing. IEEE Communications Standards Magazine 4 (4), 42–48.
Wu, F., Zhang, X.-P., Ju, P., Sterling, M.J., 2008. Modeling and control of AWS-based wave energy conversion system integrated into power grid. IEEE Trans. Power Syst. 23 (3), 1196–1204.
Xu, L., Cartwright, P., 2006. Direct active and reactive power control of DFIG for wind energy generation. IEEE Trans. Energy Convers. 21 (3), 750–758.
Xu, Y., Liu, W., Gong, J., 2011. Stable multi-agent-based load shedding algorithm for power systems. IEEE Trans. Power Syst. 26 (4), 2006–2014.
Yan, Y., Qian, Y., Sharif, H., Tipper, D., 2013. A survey on smart grid communication infrastructures: motivations, requirements and challenges. IEEE Communications Surveys & Tutorials 15 (1), 5–20.
Yang, P., Tan, Z., Wiesel, A., Nehorai, A., 2013. Power system state estimation using PMUs with imperfect synchronization. IEEE Trans. Power Syst. 28 (4), 4162–4172.
Yang, C.-W., Dubinin, V., Vyatkin, V., 2019. Automatic generation of control flow from requirements for distributed smart grid automation control. IEEE Transactions on Industrial Informatics 16 (1), 403–413.
Yazdani, A., Dash, P.P., 2009. A control methodology and characterization of dynamics for a photovoltaic (PV) system interfaced with a distribution network. IEEE Trans. Power Deliv. 24 (3), 1538–1551.
Yoshida, H., Kawata, K., Fukuyama, Y., Takayama, S., Nakanishi, Y., 2000. A particle swarm optimization for reactive power and voltage control considering voltage security assessment. IEEE Trans. Power Syst. 15 (4), 1232–1239.
You, H., Vittal, V., Yang, Z., 2003. Self-healing in power systems: an approach using islanding and rate of frequency decline-based load shedding. IEEE Trans. Power Syst. 18 (1), 174–181.
Yuan, X., Chen, Z., Yuan, Y., Huang, Y., 2015. Design of fuzzy sliding mode controller for hydraulic turbine regulating system via input state feedback linearization method. Energy 93, 173–187.
Zhabelova, G., Vyatkin, V., 2012. Multiagent smart grid automation architecture based on IEC 61850/61499 intelligent logical nodes. IEEE Trans. Ind. Electron. 59 (5), 2351–2362.
Zhang, X., Chi, K.T., 2015. Assessment of robustness of power systems from the perspective of complex networks. In: 2015 IEEE International Symposium on Circuits and Systems (ISCAS), pp. 2684–2687.
Zhang, X., Soudi, F., Shirmohammadi, D., Cheng, C.S., 1995. A distribution short circuit analysis approach using hybrid compensation method. IEEE Trans. Power Syst. 10 (4), 2053–2059.
Zhang, C., Wu, J., Cheng, M., Zhou, Y., Long, C., 2016. A bidding system for peer-to-peer energy trading in a grid-connected microgrid. Energy Procedia 103, 147–152.
Zhang, C., Wu, J., Long, C., Cheng, M., 2017. Review of existing peer-to-peer energy trading projects. Energy Procedia 105, 2563–2568.
Zhong, J., Nobile, E., Bose, A., Bhattacharya, K., 2004. Localized reactive power markets using the concept of voltage control areas. IEEE Trans. Power Syst. 19 (3), 1555–1561.
Zhou, K., Yang, S., Chen, Z., Ding, S., 2014a. Optimal load distribution model of microgrid in the smart grid environment. Renew. Sustain. Energy Rev. 35, 304–310.
Zhou, N., Meng, D., Huang, Z., Welch, G., 2014b. Dynamic state estimation of a synchronous machine using PMU data: a comparative study. IEEE Transactions on Smart Grid 6 (1), 450–460.
Zidan, A., El-Saadany, E.F., 2012. A cooperative multiagent framework for self-healing mechanisms in distribution systems. IEEE Transactions on Smart Grid 3 (3), 1525–1539.
Zou, K., Agalgaonkar, A.P., Muttaqi, K.M., Perera, S., 2011. Distribution system planning with incorporating DG reactive capability and system uncertainties. IEEE Transactions on Sustainable Energy 3 (1), 112–123.
Zubo, R.H., Mokryani, G., Rajamani, H.-S., Aghaei, J., Niknam, T., Pillai, P., 2017. Operation and planning of distribution networks with integration of renewable distributed generators considering uncertainties: a review. Renew. Sustain. Energy Rev. 72, 1177–1198.