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Dynamic, Stochastic, Computational, and Scalable Technologies for Smart Grids

Ganesh K. Venayagamoorthy
Missouri University of Science and Technology

Ganesh Kumar Venayagamoorthy
Missouri University of Science and Technology, USA

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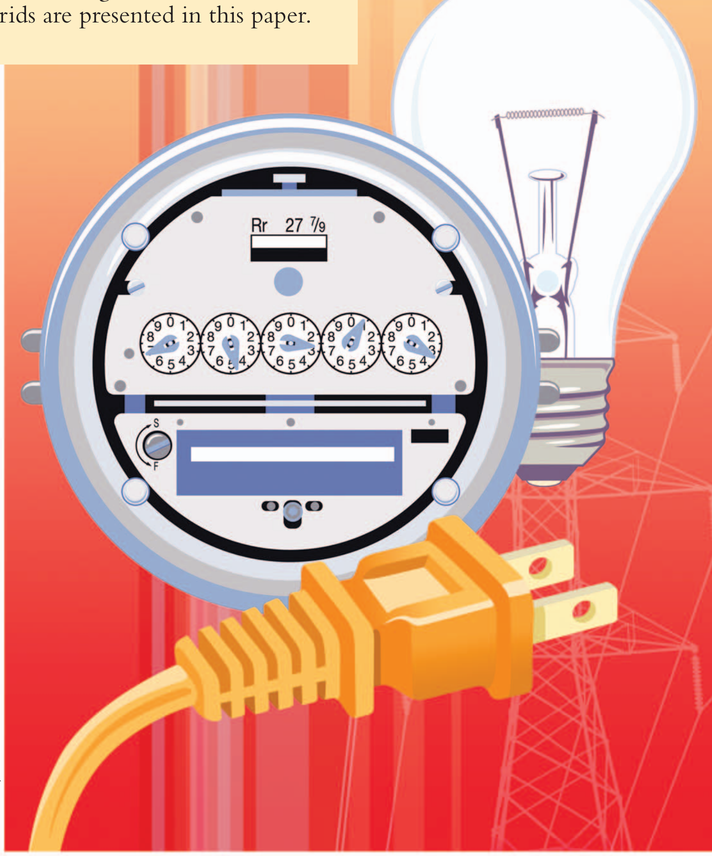
Abstract–The smart electric power grid will evolve into a very complex adaptive system under semi-autonomous distributed control. Its spatial and temporal complexity, non-convexity, non-linearity, non-stationarity, variability and uncertainties exceed the characteristics found in today's traditional power system. The distributed integration of intermittent sources of energy and plug-in electric vehicles to a smart grid further adds complexity and challenges to its modeling, control and optimization. Innovative technologies are needed to handle the growing complexity of the smart grid and stochastic bidirectional optimal power flows, to maximize the penetration of renewable energy, and to provide maximum utilization of available energy storage, especially plug-in electric vehicles.

Smart grids will need to be monitored continuously to maintain stability, reliability and efficiency under normal and abnormal operating conditions and disturbances. A combination of capabilities for system state prediction, dynamic stochastic power flow, system optimization, and solution checking will be necessary. The optimization and control systems for a smart-grid environment will require a computational systems thinking machine to handle the uncertainties and variability that exist. The importance and contributions of the computational intelligence field for developing the dynamic, stochastic, computational, and scalable technologies needed for sense-making, situational awareness, control and optimization in smart grids are presented in this paper.

I. Introduction

The North American electric power grid built several decades ago is the world's largest single machine ever built by man, and it is ranked as the number one greatest achievement of the 20th century by the US National Academy of Engineering (NAE). It is a complex adaptive system under semi-autonomous control. The complexity and interconnectivity of the electric power grid increases with all forms of distributed integration of renewable sources of energy and energy storage. The smart grid's growing complexity requires different approaches to traditional methods of modeling, control and optimization in power systems. These new approaches need either to be augmented with existing ones or completely replaced in some cases, providing capabilities for rapid adaptation, dynamic foresight, sense-making, situational awareness, fault-tolerance and robustness to disturbances and randomness.

The NAE committee on Engineering Grand Challenges has identified 14 areas awaiting solutions in the 21st century,



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Smart grid's growing complexity requires different approaches to traditional methods of modeling, control and optimization in power systems.

including solving energy problems, reverse engineering the brain, and securing cyberspace [1]. All these tasks are very important for realizing a true smart grid in 21st century.

In many parts of the world today, the electric power infrastructure is a major area of research and development, especially given the introduction of smart grid technologies and task forces [2]-[6]. Professional societies across the world have launched task forces and working groups [7]. The IEEE Computational Intelligence Society launched its smart grid task force in October 2010 with members from many IEEE regions [8].

The smart grid can be viewed as a digital upgrade of the existing electricity infrastructure to allow for the dynamic optimization of current operations as well as the incorporation of dynamic gateways for alternative sources of energy production and storage. A smart grid [9], sometimes referred to as the Intelligent Grid/*Intelligrid* and *FutureGrid,* must have certain basic functions for modernization of the grid (as indicated in the Energy Independence and Security Act of 2007) [2], including:

- ❏ Having a self-healing capability.
- ❏ Being fault-tolerant by resisting attacks.
- ❏ Allowing for the integration of all energy generation and storage options, including plug-in electric vehicles.
- ❏ Allowing for the dynamic optimization of grid operation and resources with full cyber-security.
- ❏ Allowing for the incorporation of demand-response, demand-side resources and energy-efficient resources.
- ❏ Allowing electricity clients to actively participate in grid operations by providing timely information and control options.
- ❏ Improving the electricity infrastructure's reliability, power quality, security and efficiency.

In order to carry out the functions mentioned above, intelligent systems that increase and provide the ability to monitor, forecast, plan, learn, understand complexity, share understanding across neighboring areas, schedule, make decisions and take appropriate actions to ensure stability, reliability and efficiency of an electric power grid are required. Intelligent technologies that show promise and have the potential to achieve smart grid goals are more likely to be those that are Dynamic, Stochastic, Computational and Scalable (DSCS). DSCS technologies are important to achieve Global Dynamic Optimization (GDO) of the electric power grid.

The Electric Power Research Institute (EPRI) and the US National Science Foundation (NSF) co-sponsored an international workshop on GDO of the electric power grid in April 2002 in Playacar, Mexico [10]. At this meeting, some challenges and potentials were brainstormed. Computational intelligence and adaptive critic designs were presented as a promising potential approach for GDO. Four years later, NSF sponsored a workshop on Approximate Dynamic Programming (ADP) in Cocoyoc, Mexico [11], [12]. In this workshop, Werbos presented the challenge of how to build/understand systems with truly brain-like intelligence [13]. In 2007, the NSF Office of Emerging Frontiers in Research and Innovation solicitated proposals on the topic of Cognitive Optimization and Prediction: From Neural Systems to Neurotechnology (COPN) under program directorship of Werbos. *Neuroscience and Neural Networks for Engineering the Future Intelligent Electric Power Grid* (the *Brain2Grid* project) was one of four COPN proposals selected for funding [14].

The importance and contributions of the Computational Intelligence (CI) field in developing DSCS technologies that can smarten the electric power grid (smart grid) are described in this paper [15], [16]. Section II of this paper briefly introduces the concept of computational systems thinking and the role of CI in the development of a Computational Systems Thinking Machine (CSTM). Sections III to V describe typical smart grid problems where CSTM with DSCS technologies are required, and how CI-based approaches address some of the complex smart grid challenges.

II. Computational Systems Thinking

Systems thinking is an approach to understanding how components in a system influence each other within an entirety and where solutions are derived based on coupled dynamics [17]. Computational methods and models enable us to solve complex problems that seem impossible otherwise. Computational thinking builds on the power and limits of computing processes [18]. Computational systems require three strands of thinking to handle an evolving, uncertain, variable and complex environment such as the smart grid; these are systems thinking for *sense-making*, systems thinking for *decision-making,* and systems thinking for *adaptation*. In other words, there are sense-making agents, decision-making agents and adaptation agents. These agents are also referred to as the communication, computation and control (C^3) agents, respectively. In the center of all this systems thinking is the real-time wealth of knowledge that continuously evolves and refines itself as the system undergoes changes. The knowledge well learns and unlearns facts and insights over time. A single computational systems thinking machine is shown in Fig. 1. Note that for a smart grid, several of these will co-exist in harmony while coordination and communication are enabled between similar and different agents. Collaboration between co-existing agents is essential for sense-making, decision-making and adaptation. In other words, collaborative computational systems thinking is needed between levels – horizontally and vertically.

Computational intelligence and Adaptive Critic Designs (ACDs) are important in developing a true CSTM. CI is the study of adaptive mechanisms to enable or facilitate intelligent behavior in complex, uncertain and changing environments [19]. These adaptive mechanisms include those

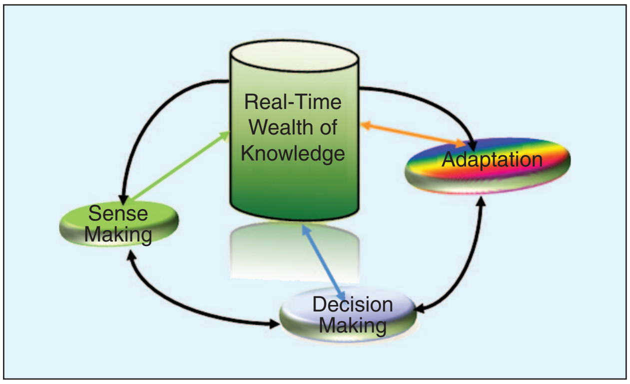

FIGURE 1 CSTM – the integrated cycle of sense-making, decision-making and adaptation. The knowledge base is the domain of expertise evolved continuously with experience accumulated.

nature-inspired and artificial intelligence paradigms that exhibit an ability to learn or adapt to new situations, to generalize, abstract, discover and associate. The typical paradigms of CI are neural networks, immune systems, swarm intelligence, evolutionary computation and fuzzy systems, as illustrated in Fig. 2 [20]. These paradigms can be hybridized to form neuro-fuzzy systems, neuro-swarm systems, fuzzy-PSO systems, fuzzy-GA systems, neuro-genetic systems, etc., as shown in Fig. 2. The hybrids are superior to any one of the paradigms in one or more ways [21].

ACDs, proposed by Werbos and based on combined concepts of reinforcement learning and approximate dynamic programming, are powerful approaches for the control and optimization of complex systems [22], [23]. ACDs use neural network (critic and action network) based designs for optimization over time and for solving the Hamilton-Jacobi-Bellman equation of optimal control. The critic network approximates the cost-to-go function J of Bellman's equation of dynamic programming (1) and is referred to as the heuristic dynamic programming (HDP) approach in ACDs,

$$J(t) = \sum_{k=1}^{\infty} \gamma^k U(t+k), \tag{1}$$

where γ is a discount factor between 0 and 1, and $U(t)$ is a utility/reward function or a local performance index. The action network provides optimal control to minimize or maximize the cost-to-go function J. There are different members of the ACD family that vary in complexity and power [24].

A hybrid approach consisting of conventional and CI-ACD technologies is sufficiently powerful to develop a CSTM for a smart grid. CI attributes towards a CSTM are illustrated in Fig. 3.

III. Intelligent Sense-Making and Situational Awareness

Sense-making is the process by which individuals attach a meaning to an experience. Sense-making is at the heart of learning cognitive skills and often must occur in highly uncertain situations. Gathering more information does not always reduce uncertainty. Other concerns reside with the information sensed. Is it trustworthy? Is it controversial or contrary to what is known? If so, then the data to be analyzed becomes complex. In the smart grid environment, depending on the type of decisions and controls, the time to act upon the understanding derived may be limited. Recognizing/identifying the right dots in the data (and information) is the critical component to time constrained sense-making. An important characteristic that a CSTM should possess is its ability to transform 'data' into 'information,' 'information' into 'knowledge,' and 'knowledge' into understanding' at their respective levels and in a timely manner (Fig. 4). For example, based on actual and predicted wind speeds across geographical locations, a CSTM should be able to dynamically project and dispatch power flows in a smart grid to (from) energy storage in order to accommodate excess (deficits) in wind power generation. For different system disturbances, a CSTM should have capabilities to predict the modal frequencies that would be excited based on sensor data, such as phasor measurements, and in-turn coordinate power oscillation damping controllers to suppress the critical modes.

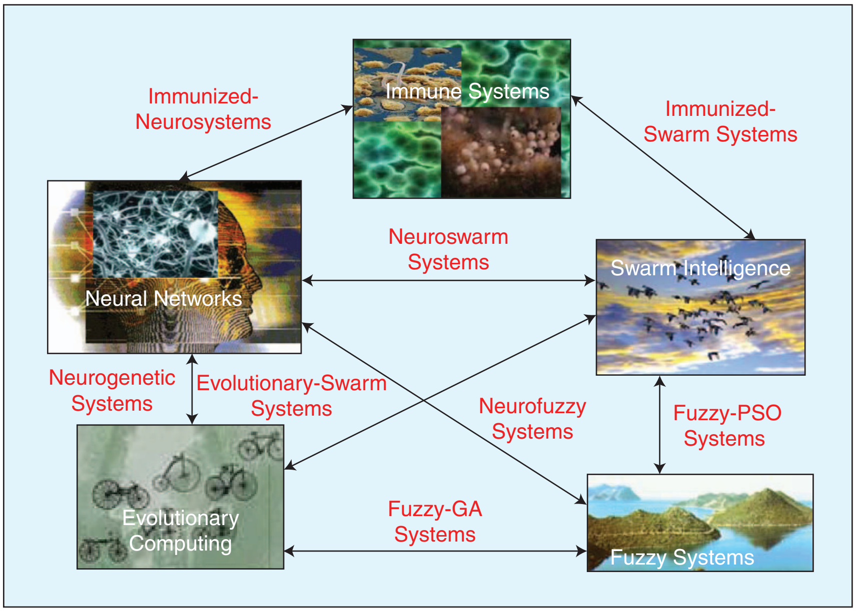

FIGURE 2 Main paradigms of CI and their hybrids [20].

Situational awareness is critical for secure and efficient smart grid operation. A general definition of situational awareness (SA) is that it is the perception of environmental elements within a volume of time and space, the understanding of their meaning, and the prediction of their states in the near future. SA by control room operators is of great importance for secure operation of the electric power grid. Despite the importance of analytical methods, continuous data sense-making is critical for ensuring the stability of the smart grid. It is said that more information (a lot of data) does not necessarily matter in critical operations; rather, what is important is to prioritize the understanding of what matters at the respective instances. It is also critical that an understanding be gained from a shared view because the power grid is interconnected, and its dynamics are spatially and temporally connected. Researchers at the Pacific Northwest National Laboratory (PNNL) introduced new ways of looking at the problem of SA to increase awareness of grid operators [25].

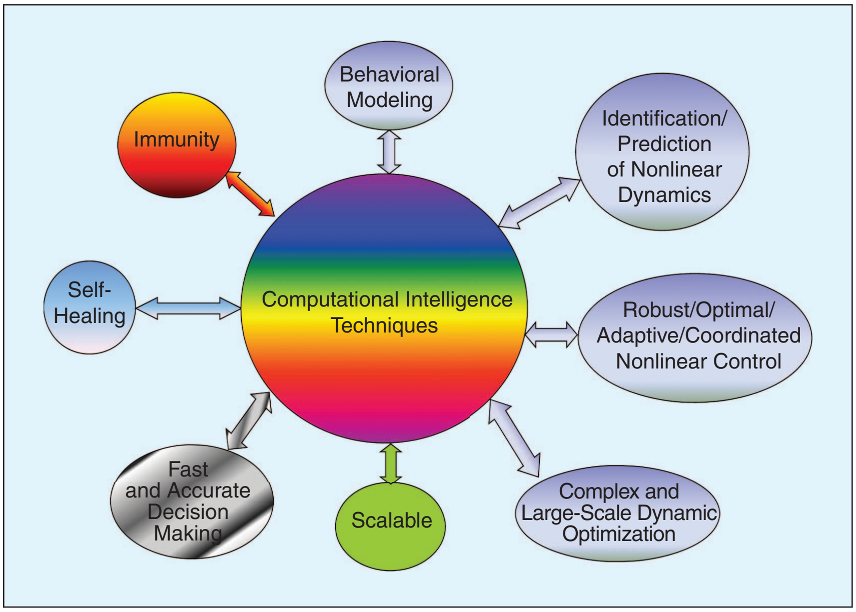

FIGURE 3 CI attributes towards development of a CSTM.

Accurate and timely communication of states of generation, transmission and distribution systems is critical for ensuring the stability of interconnected smart electric power grids. The report on the Northeast Blackout on August 14, 2003, shows that it was difficult to get reliable information from the state estimation software/simulations, contingency analysis results, and critical status of power lines relating to the status of systems outside of the individual areas [25]. A failure in SA occurred mainly to due to a lack of shared information across control areas, leading to a cascaded blackout.

In the following subsections, forecasting, voltage stability monitoring, real-time stability assessment, and maintenance scheduling are discussed.

Forecasting: Forecasting dynamic loads and sources of electric energy is necessary for smart operations of the grid. Unit commitment and economic (and emission) dispatch are carried out based on load forecasting [26]. Typically, the amount of the load depends on a number of factors, including time of the day, day type (weekday or weekend), temperature, humidity, season and location. Several classical techniques, such as regression analysis, statistical methods and time series analysis, have been tested but ultimately ruled out due to their limited accuracy [27]. CI techniques have been studied extensively and appear to provide accurate load predictions [28]. This is one of the successful areas where CI-based software is commercially available and is used extensively by many utilities all over the world [29].

When alternative sources of energy are connected to a power grid, be it wind or solar farms, dynamic load and electric energy at a given time must be forecasted in order to carry out an efficient and economical operation of a smart grid. Predicting solar and wind power is a complex problem due to high spatial and temporal dependencies that cause variability and uncertainties. CI-based hybrid approaches have been shown to be promising tools for wind and solar energy predictions [30], [31]. Recurrent neural networks can be used for characterizing and modeling the performance of wind and solar system installations. These characterization systems simultaneously use weather data and performance data over a period of time to learn the input/output relationships between weather and system performance [32]. Such systems will become necessary in smart grids for energy and load dispatch as renewable source installations spread widely.

Voltage Stability Monitoring: Voltage stability awareness has become an issue of great concern for both power system planning and operation in recent years as a result of a number of major blackouts experienced in many countries due to voltage stability problems. These problems are due mainly to power systems being operated closer to their stability limits because of increased demand for electricity [33]. A comparative study and analysis of six different voltage stability indices was presented in [34]. Neural networks have shown promise for voltage stability monitoring. A new method to estimate the voltage stability load index (VSLI) at each load bus based on synchrophasor measurements of voltage magnitudes and angles at load buses using echo state networks (ESNs) was reported in [35]. Figs. 5 and 6 show the application of an ESN for VSLI estimation in an IEEE14 bus system, and the estimation of VSLIs at the different load buses with an outage of one of the system's parallel transmission lines [35].

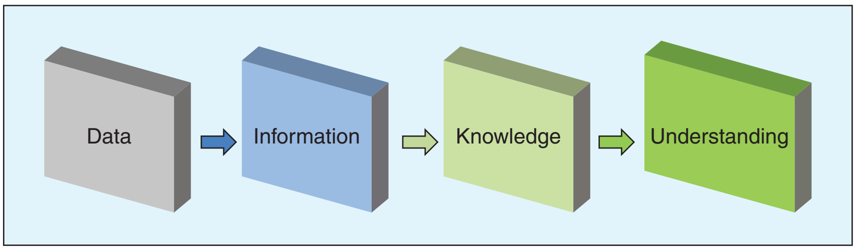

FIGURE 4 Transforming data into understanding by the sense-making strand of a CSTM.

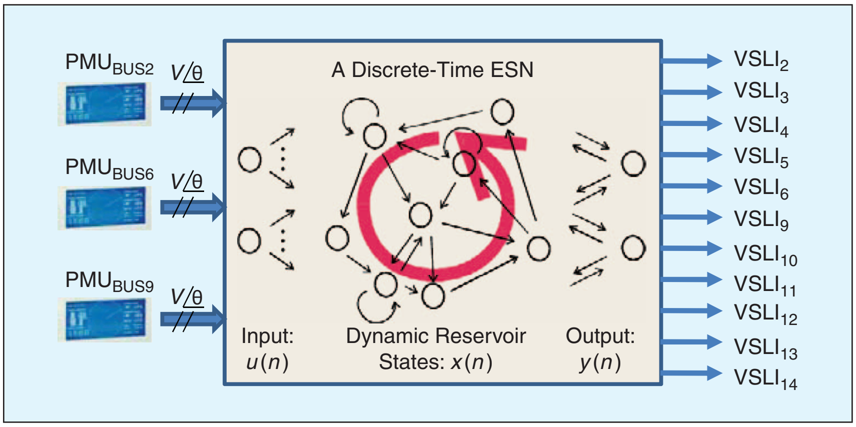

FIGURE 5 VSLI estimation using echo state networks.

technology is required to estimate and predict the current and future states of the grid, respectively, through a network index. Fuzzy logic is a suitable CI approach for realizing a single network stability index. Such an approach further allows a system operator to dissect the network index to its constituents (such as angle stability index, voltage stability index and frequency stability index) made up of several lower levels. The impact of switching in and out of power system oscillation damping controllers, voltage compensation devices and energy storage can be visualized through such a real-time assessment engine in a control room.

Real-Time Stability Assessment: Real-time stability assessment (RT-SA) of power systems is a challenging and important problem in electric utility today and is expected to become even more important with smart grids. Some key challenges associated with RT-SA [36] are: the large numbers of contingencies and sequences of events that are typically needed to provide accurate SA; the wide range of operating conditions and topology of the power system that make the operating space very complex; the speed with which the SA can be assessed in real-time; the large number of measurements available in the power system; the lack of methods to enhance the correlations between measurements and SA; and the lack of an effective assessment index. The application of neural networks to dynamic security contingency screening and ranking is summarized in [37].

The RT-SA of a power system is an important smart grid initiative towards achieving better energy stability, security, efficiency and emergency resilience in the presence of generation outages (reflecting $N-1, N-2, \ldots, N-k$ contingencies), and better handling load shedding (load outages), major system perturbation (through faults), and topology changes (transmission line outages). First, this requires wide-area measurements, dynamic system models, and evaluations of various stability limits to be performed faster than real-time on high-speed computing platforms. Thereafter, an intelligent sense-making

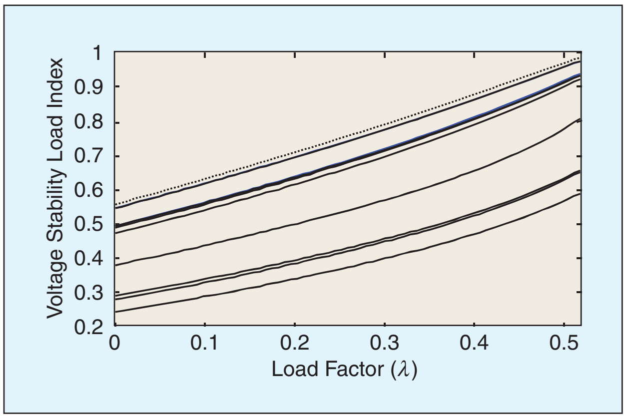

FIGURE 6 ESN-based VSLI estimation at different load buses in an IEEE14 bus system with a transmission line outage.

Maintenance Scheduling: One of the visions for a smart grid is for it to optimize assets and operate efficiently. Today's grid has minimal integration of limited operational data with asset management processes and technologies. Grid technologies that are effectively integrated with asset management processes lead to effectively managed assets and costs [38]. Maintenance scheduling is part of asset management functions. Generator Maintenance Scheduling (GMS) for a large power system has become a complex, multi-objective, constrained optimization problem with an increased number of generators and a low reserve margin. CI-based approaches, including genetic algorithms and particle swarm optimization (PSO), have been applied to solve this complex optimization problem [39]. With the integration of wind farms, the GMS problem becomes even more complex. A modified discrete PSO (MDPSO) was applied to solve this stochastic optimization problem considering uncertainty in wind power generation over the entire maintenance horizon. Studies conducted on a Nigerian power system with potential wind farms showed annual cost savings and enhanced CO_2 emission reduction for different GMS scenarios (see Fig. 7).

IV. Monitoring and Control

The general configuration of a modern power system features widely-dispersed power sources and loads. The inherent nonlinearity in the system becomes a major source of model uncertainty, which includes inaccuracies in modeling the power system devices such as the transformers, the transmission lines and the loads. The loads are dynamic and continuously changing. Final control settings are made using field tests at a couple of operating points of the power system on the distributed control devices. The increasing complexity and highly nonlinear nature of a smart grid requires an online monitoring system that is real-time and accurate. This provides a better understanding of the dynamic and complex behavior of a smart grid. The monitoring systems should cover both local and wide areas. Based on a real-time online model, controllers that operate locally and on a wide area can be adapted and made intelligent to sense the operating conditions and generate the right action signals. Neural networks can serve as a universal, dynamic system representation, and they are great at input-output modeling, especially for highly non-linear systems. Neural networks, which represent an extremely successful solution inspired by biology, are very versatile in the tasks they can solve. In the following subsections, distributed local monitoring and control, wide-area monitoring and control, and dynamic stochastic optimization in power systems are discussed.

Distributed Local Monitoring and Control: Many researchers have reported several CI-based approaches that demonstrate utility for improving the control performances of power system elements, including synchronous generators [40], [41], wind turbine generators [42], and Flexible AC Transmission Systems (FACTS) [43]. For example, multilayer perceptrons (MLPs) and radial basis functions (RBFs) with time delays are able to identify/model multiple-input-multiple-output time varying systems as synchronous generators [40]. With continuous online training, these models can track the dynamics of these systems, thus yielding adaptive identification for changes in operating points and conditions. Adaptive online identification provides up-to-date system modeling to adapt controller parameters, thus providing the desired control signals for a given disturbance. The successful implementation of these networks for adaptive and optimal control of turbogenerators has been reported by the author on digital signal processors [44]. Fig. 8 shows a Dual Heuristic Programming (DHP) based

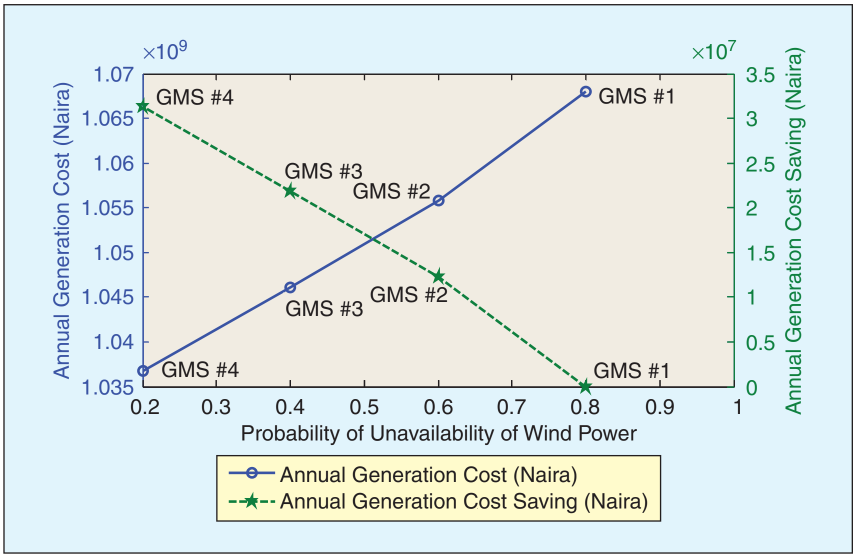

FIGURE 7 Annual generation cost and savings for different GMS and probabilities of unavailability of wind power.

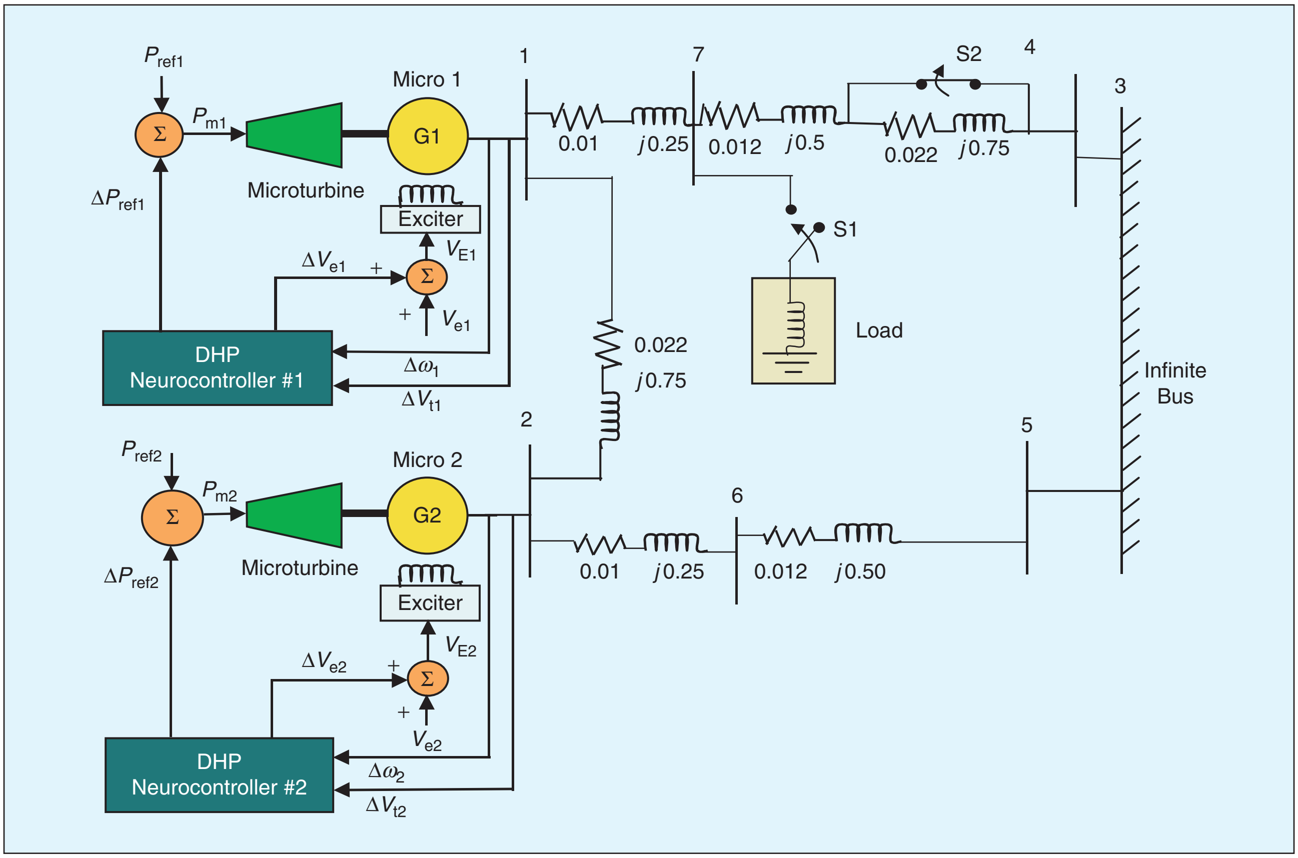

FIGURE 8 Multimachine power system consisting of turbogenerators G1 and G2 controlled by DHP neurocontrollers.

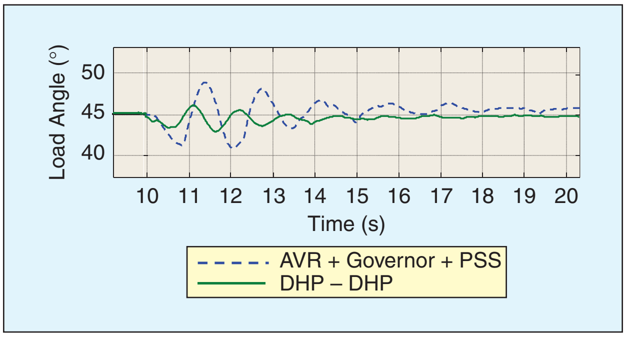

FIGURE 9 Comparison of DHP controllers with conventional controllers (AVR+Governor+PSS) on generator G2 (Fig. 8) under a short circuit fault in close proximity to generator G1.

excitation and turbine controller on the generators in a multimachine power system. This DHP controller performs the functions of an Automatic Voltage Regulator (AVR), governor and Power System Stabilizer (PSS). Fig. 9 shows the load angle of generator G2 (Fig. 8) with DHP neurocontrollers on generators G1 and G2 compared to conventional AVRs, governors and a power system stabilizer (on generator G1) when a three phase 125 ms short circuit fault was applied in proximity to generator G1. It is clear that adaptive, critic-based neurocontrollers (with fixed optimal weights) can still outperform the conventional PID and lead-lag controllers with changes in operating conditions.

A new adaptive control strategy (shown in Fig. 10) for a Distribution Static Compensator (DSTATCOM) based on an Artificial Immune System (AIS) to reduce the impact of pulse loads on bus voltage, thus keeping it at desired level, was presented for an electric ship power system (categorized as a small microgrid) in [45]. Most of the CI techniques are offline and require prior knowledge of the system's behavior. But AIS, which is inspired by theoretical immunology and observed immune functions, principles and models, has the potential for online adaptive system identification and control. Abnormal changes in the system's response are identified and acted upon without having any prior knowledge [46]. The AIS-based DSTATCOM controller exhibits innate and adaptive immune system behaviors. Innate response is for common disturbances and requires optimal controller parameters. The innate controller parameters (optimal PI controller parameters) can be determined using an algorithm like PSO. The adaptive response is for new and unusual disturbances and requires adaptive controller parameters. The AIS strategy is applied for adaptation of these parameters. Fig. 11 shows the impact of an AIS-based adaptation of the PI controller parameters on a bus voltage and controller parameter variations under a pulse load. The beauty of such an adaptive controller is that the original optimal controller parameters are restored as the system returns to normality. This is unique for an adaptive controller. Such AIS-based adaptive controllers have potential for intelligent control of the many foreseeable power electronic devices in a smart grid.

The control of electric power systems relies on the availability and quality of sensor measurements. However, measurements are inevitably subject to faults caused by broken or bad connections, bad communication, sensor failure, or malfunction of some hardware or software. These faults, in turn, may cause power system controllers to fail and consequently may lead to severe contingencies in the power system. To avoid such contingencies, a sensor evaluation and (missing sensor) restoration scheme (SERS) accomplished using auto-associative neural networks (auto-encoders) and particle swarm optimization was developed in [47]. Based on the SERS, a missing-sensor-fault-tolerant control (MSFTC) was developed for controlling a static synchronous series compensator (SSSC) connected to a power network. This MSFTC improved the reliability, maintainability and survivability of the SSSC and the power network. Such fault-tolerant technologies will be needed in a smart grid to improve its reliability and security.

Wide-Area Monitoring and Control: Local controllers can provide good performance when local measurements supply all the information about the effect of disturbances. But, if there are interactions between multiple adjacent areas of the power system, a wide-area-based measurement has the potential to provide better stabilizing control [48], [49]. The Wide-Area Control System (WACS) coordinates the actions of a number of distributed agents using SCADA (Supervisory Control And Data Acquisition), PMUs (Phasor Measurement Units) or other sources providing wide area dynamic information [49].

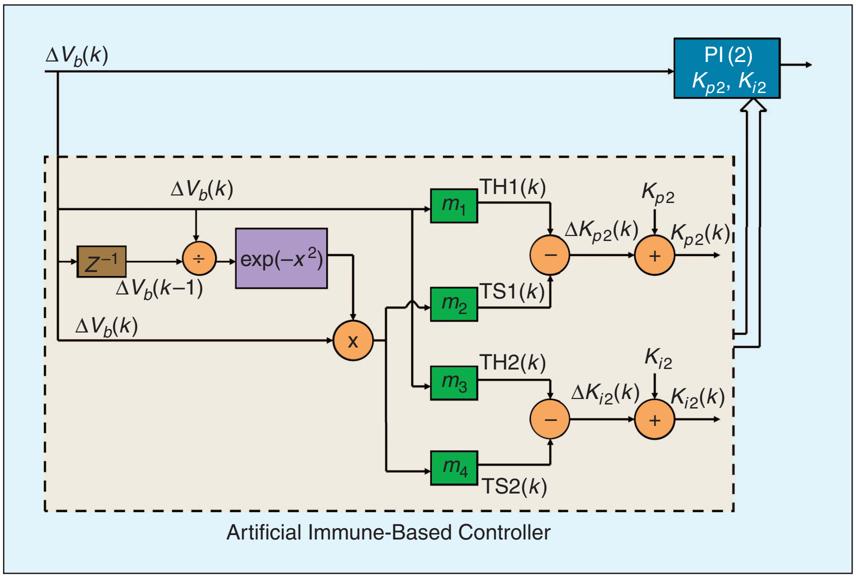

FIGURE 10 AIS-based controller for a DSTATCOM [45].

Classical designs, including observer-based state feedback, Linear Matrix Inequality (LMI), gain scheduling and H^{∞}-based damping controls, require a nominal model of the system, which might not be simple to obtain in practice with an acceptable degree of accuracy. An alternative solution is to adopt a design strategy based solely on available measurements [50].

ACDs utilize the approximation capabilities of neural networks to develop optimal controllers from disturbance measurements of available system inputs and outputs. ACD methods yield a fixed controller structure, which is comparable to other classical optimal controller designs. The primary differences are (1) ACD yields a nonlinear controller, while classical optimal designs typically provide linear controllers; (2) classical methods rely on a linear model of the system, while ACD can have a measurement-based design. ACD-based WACS have been demonstrated to be superior on several power system models for maximizing system damping to inter-area oscillations by intelligently coordinating the actions of PSSs, excitation systems, and FACTS devices [50], [51]. The adaptability of simultaneous, recurrent neural network-based WACS allows them to compensate for varying communication delays in remote measurement and control signals [52]. The performance comparison of an ACD controller with respect to two well-accepted classical designs was demonstrated on a 16-machine, 68-bus power system. A damping controller was designed to enhance damping of the three critical inter-area modes (0.39 Hz, 0.50 Hz and 0.62 Hz) present in the system with the Thyristor Controlled Series Capacitor (TCSC). The development of a Heuristic Dynamic Programming ACD neurocontroller is illustrated in Fig. 12(a). The training details of the CRITIC, IDENTIFIER and

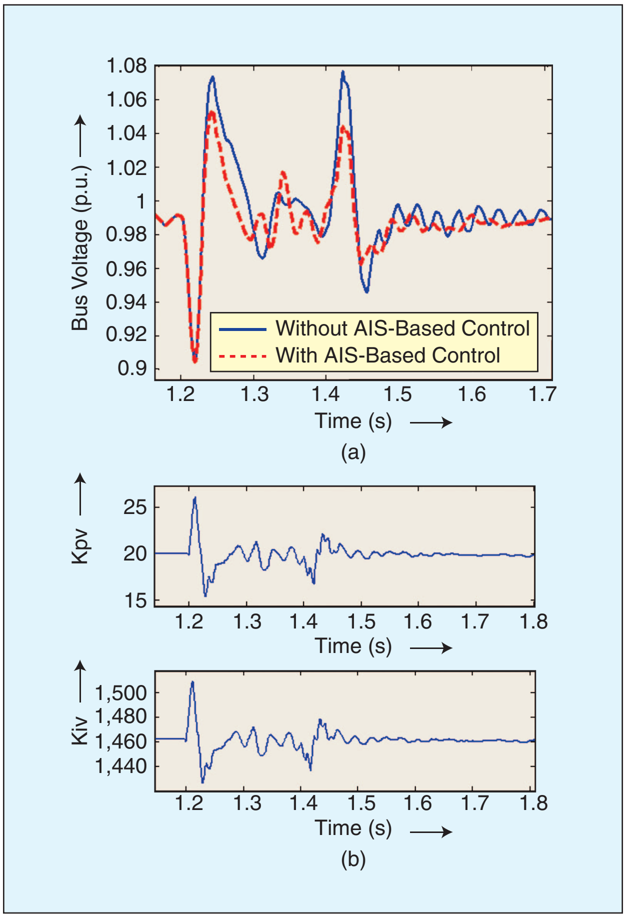

FIGURE 11 (a) Performance comparison between PSO (without AIS) and AIS-based controller for 20 MW/50 MVAR pulse load (b) Variation of PI controller proportional and integral gains (Kpv and Kiv) [45].

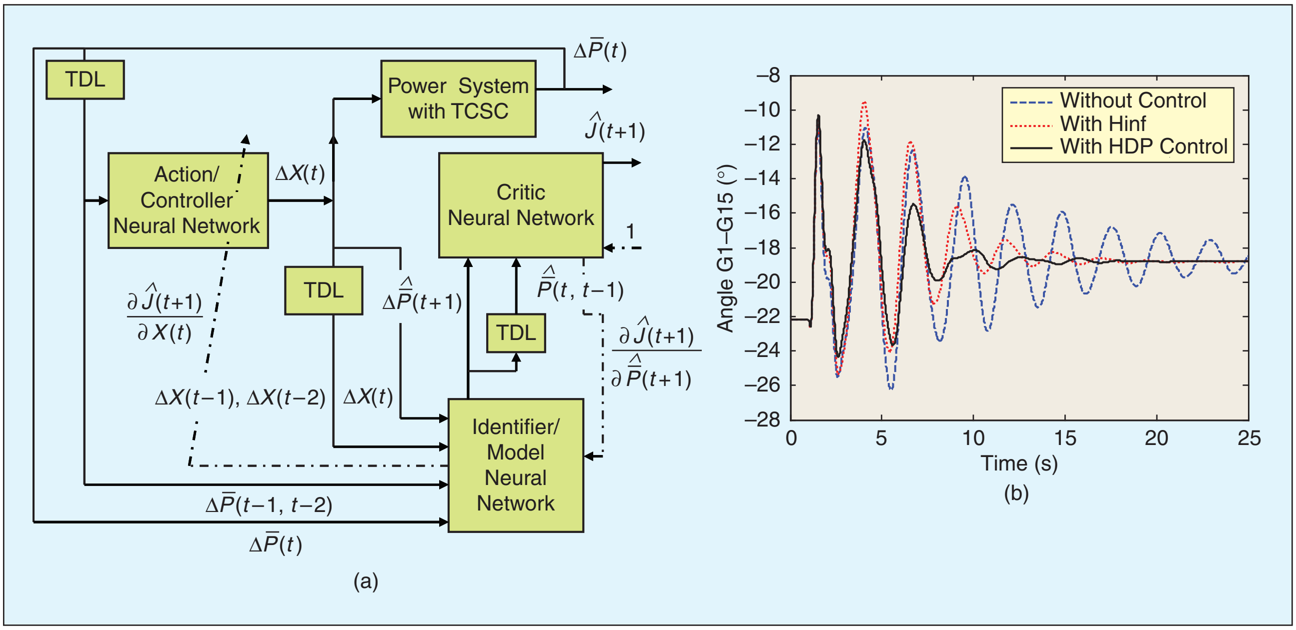

FIGURE 12 (a) HDP optimal neurocontroller design (TDL is time delay lines) (b) Oscillation in the angle difference between G1 and G15 for a 3-Φ line to ground fault and transmission line outage with H^{∞} and HDP controllers [50].

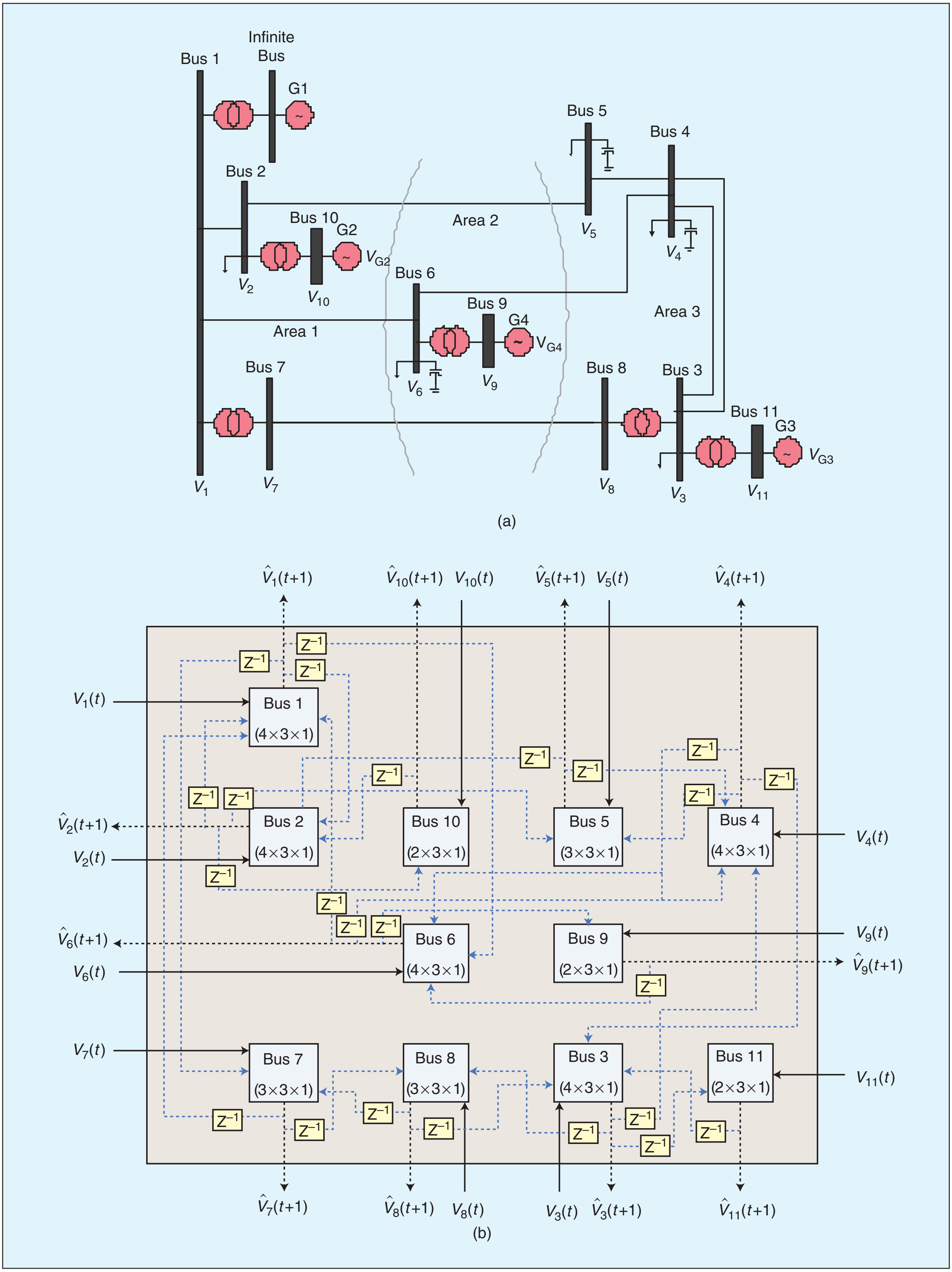

FIGURE 13 (a) A 12-bus multimachine power system (b) CNN representation of a 12-bus power system.

CONTROLLER are given in [50]. Fig. 12(b) shows three responses, namely: a) without any damping controller, b) with a damping design based on Linear Matrix Inequality (LMI), and c) with H-infinity robust control design for a 3-Φ line to ground fault placed at bus 53 for 80 ms and cleared by opening transmission line 27-53 permanently, thereby changing the post-fault topology of the power system.

If disturbance and ambient measurement data are available for a given system, an ACD controller can provide superior performance with minimum *a priori* knowledge of system states and operating regions. The main advantage of this approach is that it does not require a complete model of the system or state-estimators. The IDENTIFIER (Fig. 12(a)), based on input and output measurements, is able to identify the relevant system dynamics needed to design an optimal controller.

The successful development of a WACS depends on the predictive performance of a Wide-Area Monitoring System (WAMS). The objective of WAMS is to learn the dynamic intra-area and inter-area system information based on some sampled system input and output measurements, for example, speed deviations of generators and/or power flows in transmission lines. Neural networks, such as ESNs, are good at capturing wide-area system dynamics.

With a smart grid's plug-and-play capabilities, in order to allow for several distributed sources of energy that will connect and disconnect at different times, it is anticipated that the change in system dynamics may be erratic. A scalable approach to the development of WAMS and WACS to function in a truly smart-grid environment is required. This requires an ability of neural network architectures to handle many variables concurrently, a fast learning time that is independent of the number of variables monitored and devices controlled, and a high degree of accuracy and optimality to be maintained in prediction and control, respectively.

Cellular neural networks (CNNs) have shown promise as scalable neural network architectures for handling the complexities of power systems/smart grids. The CNN architecture allows for accurate system equivalent modeling and fast prediction. The voltage dynamics of a highly interconnected power system can be directly replicated by the connections between the cells of the CNN where the cellular connections represent the transmission lines connecting the buses of the power system. A 12-bus, multi-machine power system and its modeling by a CNN is shown in Fig. 13. Ideally, a CNN can be used to predict system profiles N time-steps ahead. In an online application, if a CNN can predict system voltage profiles N steps ahead, then a system operator has that much more time to implement the necessary controls or run an analysis on the system. Preliminary real-time simulation results (Fig. 14) show the performance capabilities of this technique for a single-step prediction of bus voltages and speed deviations of generators [53].

Dynamic Stochastic Optimization: A conceptual framework for applying ACDs to power system optimizations, namely Dynamic Stochastic Optimal Power Flow Control (DSOPF), was first introduced in [54] to incorporate prediction and optimization over power system stochastic disturbances. ACDs were applied to carry out dynamic optimization of several variables in an IEEE14-bus multimachine power system containing an Unified Power Flow Controller (UPFC) [55]. In addition, the identifiers and controllers were implemented as ObjectNets. The concept of ObjectNets provides a platform for scalability. The objective of the critic network is to dynamically optimize the parameters of different controllers on the power system in order to minimize the combined deviations of all generators' speeds and terminal voltages, as well as the UPFC shunt bus voltage. In other words, the global objective is to ensure transient and dynamic rotor angle and voltage stability of the generators and the UPFC shunt bus during the power system's operation. A more recent paper illustrated an optimal power flow controller using ACDs on a 12-bus power system using the DHP-ACD approach and standard recurrent neural networks [56]. Simulation results demonstrated promising steady-state and

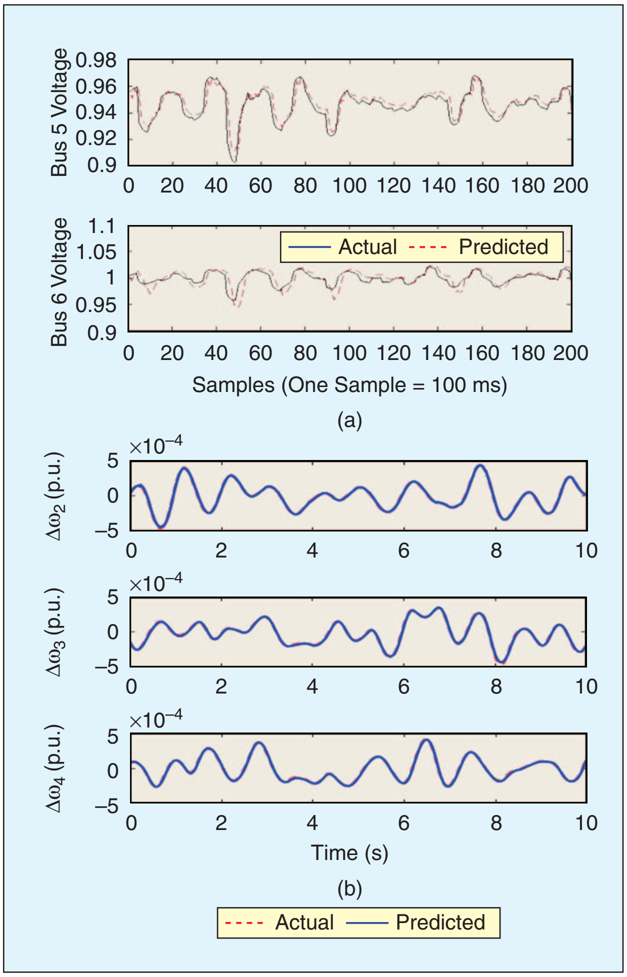

FIGURE 14 (a) CNN bus voltage predictions for transmission line outage with random perturbations applied to loads; (b) CNN-based WAM predicting speed deviations of generators.

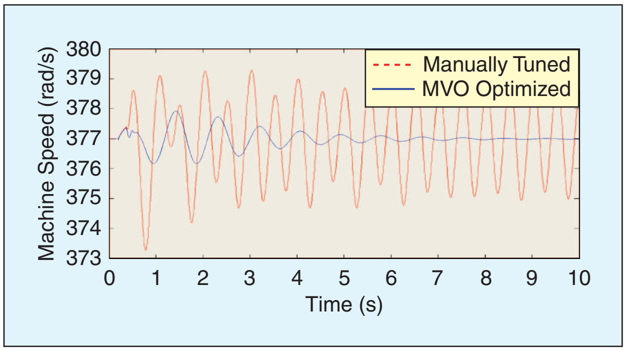

FIGURE 15 Comparison of a generator speed (rad/s) in the 12-bus system for a 10-cycle three-phase fault at the wind farm bus (when the wind speed is 13 m/s) with a manually tuned and MVO optimized RSC DFIG PI controllers.

dynamic performances of the designed DSOPF controller under various operating conditions and system disturbances.

V. Gridable Vehicles and Smartparks

As increasing numbers of Plug-in Electric Vehicles (PEVs) enter the market, the effects of adding large numbers of small power electronic devices to the grid become more and more predominant. Many of these vehicles also can be adopted to participate in Vehicle-to-Grid (V2G) applications in the proposed smart-grid framework, which calls for an increased amount of bidirectional power flows between vehicles and utility grids [57]. Typical CI applications to enhance the integration of PEVs and operation of smart grids are presented below.

Optimal Tuning of Wind Farm Controllers with SmartPark Energy Storage: The introduction of Doubly Fed Induction Generators (DFIGs) for wind turbine generators has sparked extensive research in the technology of variable-speed wind turbines. However, variations in wind speed cause a change in the transient response of the Wind Turbine Generator System (WTGS) under grid disturbances. When a DFIG-based WTGS integrated into a multimachine power system consisting of SmartParks (large number of plug-in electric vehicles in a parking lot) is subjected to severe disturbances, the resulting transients, depending on the controller parameters, can lead to a system collapse, especially when the wind power penetration fluctuation is significant. This happens

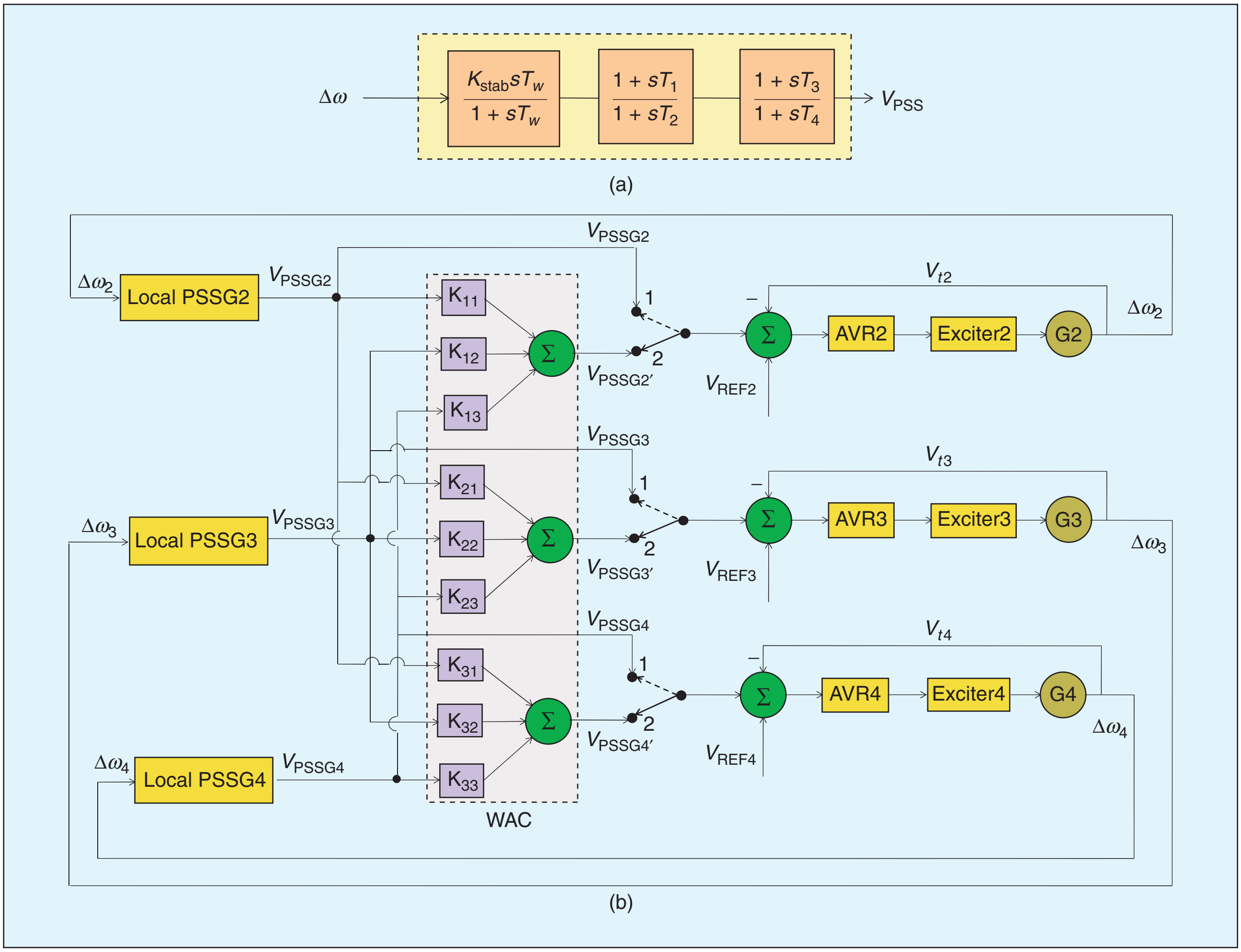

FIGURE 16 (a) Structure of local PSS and (b) structure of the WACS [59].

A large number of PEVs will significantly impact the stability of power grids.

despite whether SmartPark energy storage is charging or discharging to offset excess or compensate shortfalls in wind power, respectively. When a fault is introduced, the variable frequency converter (VFC) is the most susceptible part in DFIG-based WTGS. The VFC is controlled by a set of Proportional Integral (PI) controllers. The parameters of the PI controllers are very difficult to tune using traditional methods due to the nonlinearity of a DFIG and the increasing complexity of a smart grid. Therefore, there is a need for application of a heuristic method that is capable of intelligently tuning the PI controllers of the Rotor-Side Converter (RSC) of the DFIG.

A study was carried out on the Real-Time Digital Simulator (RTDS) to tune the PI controllers of the RSC of the DFIG in a multimachine power system consisting of SmartParks using the Mean-Variance Optimization (MVO). MVO is a new stochastic optimization algorithm [58] falling into the category of the so-called population-based stochastic optimization technique. The uniqueness of the MVO algorithm is based on the strategic transformation used for mutating the offspring based on mean-variance of a *n*-best dynamic population. Its mapping function transforms the uniformly distributed random variation into a new one characterized by the variance and mean of a *n*-best population attained so far. The search space is restricted for the algorithm to the range – zero to one, which does not change after applying the transformation. Therefore, the variables are treated always in this range, but the function evaluation is carried out in the problem range. The features of MVO make it a potentially attractive algorithm for solving many real-world optimization problems, such as tuning of PI controllers on a DFIG. When a three-phase, 167 ms fault is applied at the wind farm bus, the optimization not only improves the stability of the DFIG at a wind speed of 13 m/s system but also improves the stability of two other generators in the 12-bus, multimachine power system. Fig. 15 shows the speed of a generator with MVO optimized and manually tuned RSC PI controllers on the DFIG. With optimized parameters, the speed of the generator settles down after the fault is cleared; hence, the entire system is stable. However, with manually tuned parameters, this is not the case. Similar results have been observed at other wind speeds.

Improving Stability of a Smart Grid: Vehicles providing auxiliary services coordinate their power flows with the utility to change grid conditions in some predetermined way. If vehicle owners try to buy and sell power according to varying prices, there will be large swings in power as groups of vehicles switch the direction of their power flows. Therefore, PEVs will significantly impact the stability of power grids.

The impact of charging and discharging cycles of the PEVs connected to a 12-bus power system on the stability of the integrated system have been studied in [59]. An optimal wide-area controller for providing damping signals to the individual generators is designed based on the weighted sum of the local and global stabilizing signals using the PSO technique. The 12-bus power system, PEVs and the designed WAC (Fig. 16) are implemented in real-time on the RTDS. The design (tuning of the modulation indices) of the WAC was carried out on a DSP interfaced with the RTDS. The results with and without the WAC for moderate disturbances, like a sudden discharging of the PEVs, and also for some extreme situations, like a sudden transition from discharging to charging mode or a three phase fault during a peak charging or discharging cycle, were studied. The real-time simulation results and a Prony analysis showed that, with the PEVs connected to the power system, the WAC improves the stability of the integrated system significantly.

Scheduling Gridable Vehicles for Cost and Emission Reductions: The main sources of emissions today are from the electricity and transportation infrastructures. An objective of a Cyber-Physical Power System (CPPS) is to integrate Renewable Energy Sources (RESs) and Gridable Vehicles (GVs) to minimize cost and maximize emission reduction. Gridable vehicles are PEVs that take part in both V2G and G2V (Grid-to-Vehicle) operations. GVs can be used as loads, sources and energy storages in a CPPS. A smart grid is a large CPPS and appears complex taking in account all the conventional and green distributed energy resources, dynamic data from sensors, and smart operations needed (e.g., charging/discharging, control, etc.) from/to the grid in order to reduce both cost and emission. If a large number of GVs are connected to a smart grid randomly, peak load will be very high. The use of conventional thermal power plants to sustain electrified transportation will be economically expensive and environmentally unfriendly. Intelligent scheduling and control of energy system elements have great potential for evolving a sustainable, integrated electricity and transportation infrastructure.

A sustainable, integrated electricity and transportation infrastructure was reported in [60]. The primary contributions and emphases of this study include: i) the effectiveness of RESs and GVs for a sustainable CPPS; ii) smart and flexible charging-discharging operations of GVs as loads and sources to obtain benefits from GVs for energy storage in a sustainable CPPS; iii) maximum utilization of distributed RESs to reduce emissions in a sustainable CPPS; and iv) introduction of intelligent load leveling to reduce cost and emissions in a CPPS. Three cases listed below were studied to illustrate the effect of GVs in an integrated electricity and transportation infrastructure. Details on these models and their formulations are given in [60].

- ❏ Case 1 – random model: GVs are charged/discharged randomly;
- ❏ Case 2 – intelligent dynamic load-leveling model: GVs are charged from conventional generation using load-leveling optimization.

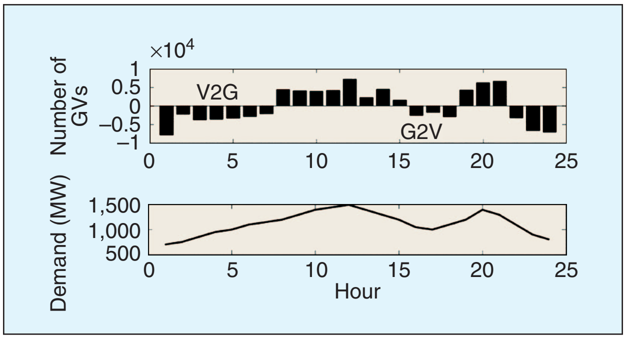

FIGURE 17 Gridable vehicles participating in V2G/G2V operations hourly in a CPPS [60].

- Case 3 – smart-grid model: GVs are charged from the grid with RESs at off-peak hours and discharged to the grid at peak hours.

Particle swarm optimization was used to minimize cost and emissions in a CPPS. The advantages of using this algorithm include: i) PSO can optimize binary, integer and real decision variables; ii) it can handle constraints; iii) it is easy to implement, fast and robust; and (iv) it balances local and global search abilities. Fig. 17 shows a V2G/G2V operation distribution schedule obtained using PSO for a 10-unit system with 50,000 GVs in a CPPS. Most of the vehicles are connected to the grid at hours 1, 12, 20, and 24 because demand is either very high or very low at those hours. V2G takes place from hours 8 to 15 and again at hours 19 to 21, when demand is high. However, G2V happens from hours 1 to 7, 16 to 18, and 22 to 24, when demand is low. Data and results are summarized in Table I for Cases 2 and 3. The smart-grid model offers maximum emission reduction.

VI. Conclusion

The electric power grid is rapidly growing, and in need of intelligent technologies for efficient, reliable and secure operation and control as the demand for electricity increases. The complexity of a smart power grid is much more than that of the traditional power grid as time-varying sources of energy and new dynamic loads are integrated into it. The smart grid demands intelligence and innovation in every area and requires an inter-disciplinary effort. Computational systems thinking capabilities are needed to provide dynamic, stochastic, computational and scalable technologies to handle the complexities, challenges and promises of smart grids. The computational intelligence community and the IEEE CIS smart grid task force have a major role to play in this era of smart grid development.

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TABLE 1 [60] Summary of input data and results of ten-unit system in CPPS.

ITEM	VALUE
TRANSPORTATION SECTOR	
AVERAGE DISTANCE COVERED BY A VEHICLE	12,000 MILES/YEAR
NUMBER OF REGISTERED GVs	50,000
AVERAGE DISTANCE COVERED BY GVs PER kWh	4.00 MILES
ENERGY NEEDED BY A GV PER DAY	8.22 kWh
ENERGY NEEDED BY 50,000 GVs PER DAY	411 MWh
TYPICAL PERCENTAGE TIME A GV IS PARKED	95%
AVERAGE EMISSION FROM A LIGHT WEIGHT VEHICLE	1.2 LB/MILE
EMISSION FROM 50,000 VEHICLES IN TRANSPORTATION SECTOR PER DAY (YEAR)	895.010 TONS (326,678 .766 TONS)
INTELLIGENT DYNAMIC LOAD LEVELING MODEL	
EXTRA EMISSION FROM POWER PLANTS TO SUPPLY ENERGY TO 50,000 GVs DURING ONE DAY (YEAR)	491.311 TONS (179,328.515 TONS)
NET EMISSION REDUCTION FROM POWER SYSTEM AND TRANSPORTATION SECTOR FOR 50,000 GVs PER DAY (YEAR)	403.699 TONS (147,35O.251 TONS)
SMART GRID MODEL: CAPITAL COST	
EXTRA ENERGY NEEDED FOR THE SMART GRID MODEL	750 MWh PER DAY
WIND ENERGY AND SOLAR ENERGY RATIO (LOCATION DEPENDENT)	2:1
CAPITAL COST OF SOLAR POWER	US$5.0/W
CAPITAL COST OF WIND POWER	US$1.0/W
SOLAR FARM SIZE (BASED ON SOME ASSUMPTION OF AVERAGE SOLAR INSOLATION)	40 MW
WIND FARM SIZE (BASED ON SOME ASSUMPTION OF AVERAGE WIND SPEED)	25.5 MW
TOTAL CAPITAL INVESTMENT FOR RESs IN THE SMART GRID MODEL WITH 5O,OOO GVs	US$225.5 MILLION
SMART GRID MODEL: BENEFITS	
EMISSION REDUCTION FROM POWER PLANTS FOR 50,000 GVs AND RESs PER DAY (YEAR)	1,233.589 TONS (450,259.985 TONS)
TOTAL EMISSION REDUCTION FROM POWER PLANTS AND TRANSPORTATION SECTOR FOR 50,000 GVs AND RESs PER DAY (YEAR)	2128.599 TONS (776,938.751 TONS)
TOTAL OPERATIONAL COST REDUCTION FROM POWER SYSTEM AND TRANSPORTATION SECTORS FOR 50,000 GVs AND RESs IN CPES PER DAY (YEAR)	$217,687.73 (US$79,456,021.45)

Note: Per year calculation is shown in the parenthesis.

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