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Neuro-Fuzzy Logic Applications for Grid Energy Management

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Abstract Grid management is becoming increasingly complex due to continuous growth in consumer demand and distributed energy resources (DERs). These two rapidly changing areas present a unique challenge when taking into consideration the mission of the United States Department of Energy being to ensure energy security through efficient, environmentally friendly, reliable, and affordable electric energy [1]. As consumer demand and DERs continue to saturate the electric grid, the problem that arises is data measurement and processing. The traditional electric grid had a one-way flow of power, whereas the modern electric grid can have bi-directional power flow via DERs and other load resources such as curtailment, load shifting programs, energy storage, to name a few. This new and rapidly developing electric grid has many more data points that will need to be processed due to the exponentially growing amount of energy resources throughout it. This means that more sophisticated management software is needed to help balance an increasingly complex electric grid. This paper will expand on traditional load management technology compared to the new concepts of neuro-fuzzy logic system managing the grid. A neuro fuzzy logic-based energy management system could be a new option to use for grid management and planning. This would allow grid operators to add additional decision processing capabilities. In this manner, the grid would be able to make complex decisions across the network rather than in specifically localized areas. This capability would allow grid operators the ability to make more efficient and reliable decisions since the system is able to process more data. This additional data could open options for the network to utilize complex responses to grid scenarios by utilizing more resources available to the network. The critical concept here is to allow more data to be processed, therefore opening more resources to be used creatively for complex grid response.

Keywords: *artificial intelligence, neural network, fuzzy logic, controls, energy management, grid management, grid modernization*

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1. Introduction

Energy is an integral factor in the development aspect of human life. This energy source, consisting of either; solar energy generation, wind energy generation, hydroelectric power generation, storage technology, biomass or solar thermal cannot be used directly in their raw forms. This raw form of energy must be converted into electricity at the generation site and transported by networks of heavy-duty electric cables, transformers, breakers, and switchyards before the consumers can use these energy resources.

The transmission of the electricity generated by these resources through mechanical and electrical hardware requires monitoring to assess the safety and ensure the reliable delivery of the energy to the necessary loads. Traditionally, engineers have developed methods and procedures to control, monitor, and manage the grid, which was unidirectional in power flow to determine the occurrence of fault and proposed remedies to these faults. Modern grid networks have evolved into conventional multidirectional energy generation and feeding sources, where grid management requires more sophisticated and complex algorithms to detect, isolate and report status of a fault on the grid. Moreover, these sophisticated systems could learn from historical faults to mitigate the fault better proactively from occurring in the future.

Smart control and decision processing technologies such as: fuzzy logic, artificial neural networks, fuzzy inference systems, etc. have been found to be an effective alternative to classical technologies. An effective and intelligent control using adaptive neuro-fuzzy inference systems (ANFIS) have been suggested by several researchers in this field [2]. Although neuro-fuzzy technology has not been widely used in grid management applications, there have been some increased applications of the use of this technology. ANFIS have been used on the basis of load frequency control in an isolated micro grid and other comparable grid controls previously.

Nazar et al. [3] investigated an ANFIS application for advanced Maximum Power Point Tracking (MPPT) control of a wind-solar standalone hybrid power generation model and used to control the power curve in the power conversion system. This article reviews the conventional load management technology compared to the new technology of managing the grid holistically, and proposes which technology should be selected for modern grid management in the power sector. During evaluation, neuro-fuzzy logic grid energy management methods will be applied to large networks consisting of distribution and transmission assets, consumers, generating resources, and DERs. This article will contribute to the application of neuro-fuzzy control in grid management. This research indicates that neuro-fuzzy controls offer a more holistic view of fault detection on the grid, making complex decision and stabilizing the electric load voltage to have consistent frequencies and magnitude that contribute to improved power quality. In this method, the evaluation will provide insight into the advantages and disadvantages of using neuro-fuzzy systems compared to conventional grid management techniques.

2. Evaluation

To evaluate the concept of neuro-fuzzy energy management, a comparison of how neuro-fuzzy networks and conventional grid management methods are used and operated will be conducted. The concept of utilizing neuro-fuzzy logic controls for electric grid management arose from a desire to incorporate logical reasoning and the intuitive decision making of an expert operator into an automated system managing a network of resources. The goal is to make decisions based on a number of learned or predefined rules, rather than numerical calculations. Neuro-fuzzy logic incorporates a rule-base structure in attempting to make decisions, while also applying machine learning and pattern recognition that allows for adaptation over time. The linguistic variable in fuzzy logic is the state in which the variables are initially designed into the system. Linguistic variables that are often used in control applications includes speed, position, corresponding error, and the derivatives of corresponding errors, as well as controls parameters such as voltage, current and temperature. The fuzzy variables are more accurately described as fuzzy linguistic qualifiers [4]. In this manner, the fuzzy qualifier performs classification of the linguistic variables as seen in Figure 1, while the neural network is processing the data based upon previously trained results.

2.1. Conventional Grid Management

The conventional power grid as shown in Figure 3, is an interconnection of various elements of electric power systems such as centralized generators, substations, transmission network, and distribution networks consisting of various consumers and DERs. Due to traditional utility perspectives of unidirectional power flow, the conventional grid is made of fewer sensors at critical locations. This makes the detection of faults and mitigation of power insufficiencies difficult and can result in longer shutdowns. These control methods are limited and thus limit the characteristics of grid responses to same degree.

Traditional grid management utilizes a PID or other similar control strategies, which have some limitations as previously introduced. PID instruments measure the error of the current state by knowing and comparing the difference between desired and actual values. The system then evaluates the decision parameters correspondingly, which consists of a rule-based decision processing platform. The calculation of error is continuously performed and serves as a baseline that allows the system to perceive its performance of mitigating power supply or power quality issues.

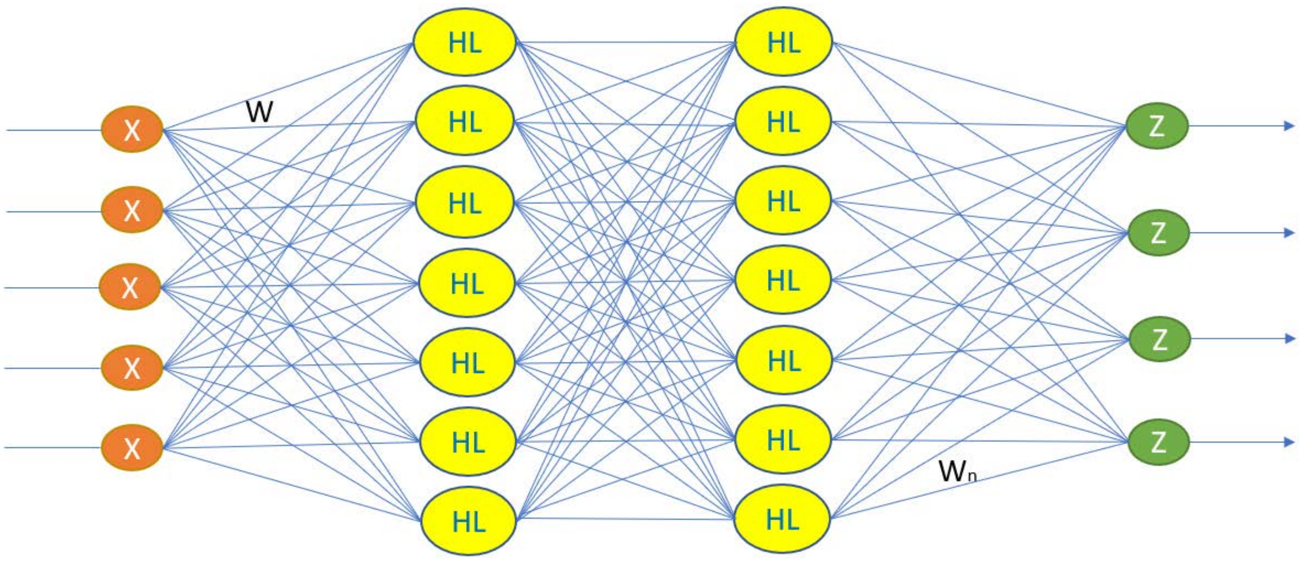


Figure 1. Illustration of how neuro-fuzzy systems work indicating X-input layer, W-weight-hidden layer, and Z output layer

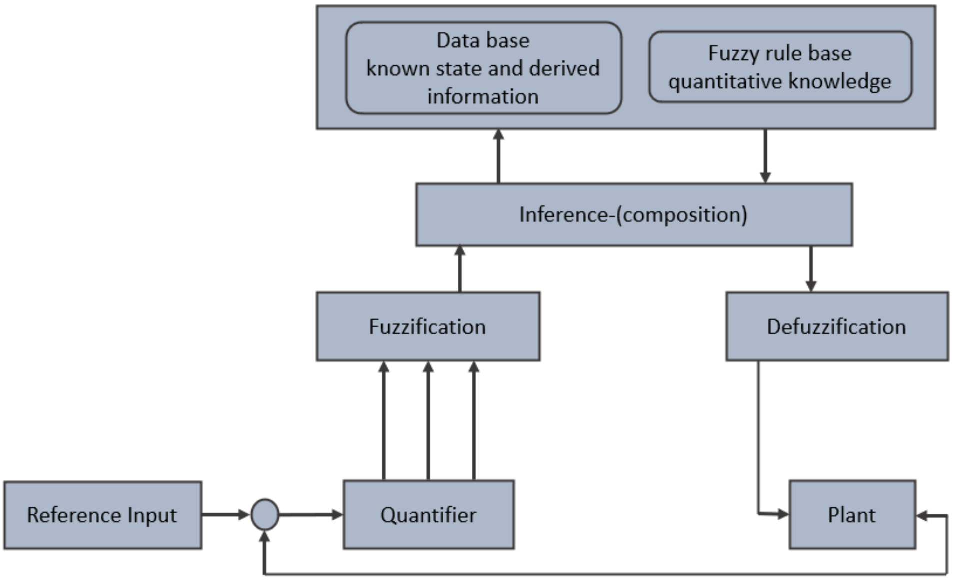


Figure 2. Illustration of neuro-fuzzy network data processing

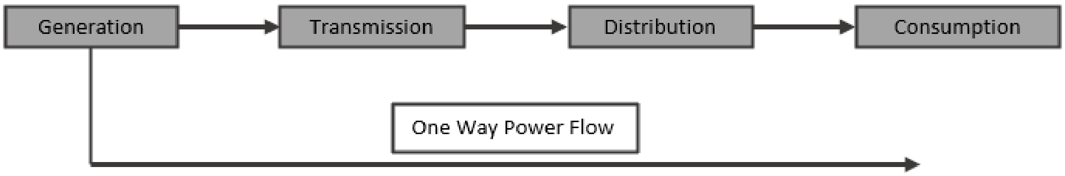


Figure 3. Illustration of conventional power flow on the electric grid

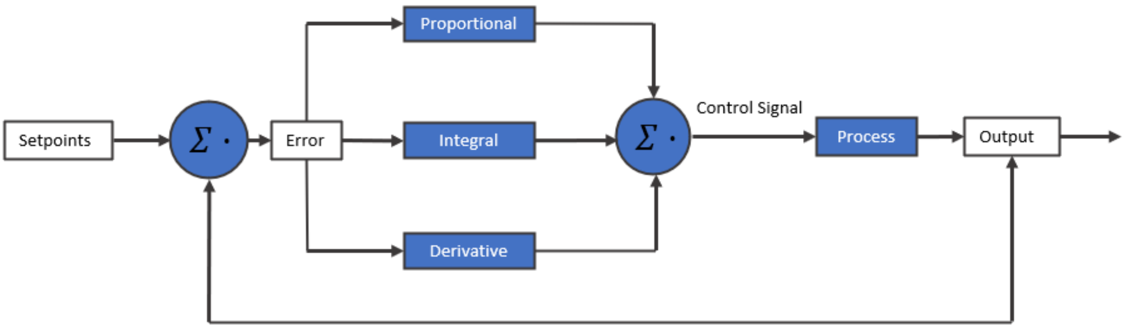


Figure 4. Block diagram of a conventional PID controller for grid energy management

3. Significance

The grid is a complex network with numerous generation and load inputs which require a control technology that will be able to sense and process a holistic view of the network to make effective decisions. As it has been discussed, PID controllers' devices are traditionally used in industrial and utility settings to control or adjust complex physical parameters of the environment such as temperature, pressure, voltage, and current of various circuits and components on the grid. This is due to its reliability to make decisions in a hard-coded rule-based system which help it to maintain these parameters at a constant or desired values. Some of the uses of the PID controllers and the limitations associated with it are listed below:

- A PID controller has been widely used as an integral part of the temperature control system of transformers. The controls' structure is relatively simple in nature, where temperature controls is a perfect application for this technology. Simply stated, the input of the PID controller is obtained from a temperature sensor and the output is fed to a fan or a heater [4]. The fan or the heater; therefore, acts as a control element. The speed of the fan or the temperature of the heater gets adjusted according to the feedback signal.
- Most manufacturing industries make use of high-capacity furnaces to melt and heat different elements. The temperature of such furnaces is required to be monitored periodically. Also, one must be able to control and vary the temperature to maintain the temperature of the furnace at the desired constant value. For this purpose, generally, a PID controller is employed.
- A PID controller is mostly used as an MPPT charge controller. The voltage and current characteristics

of a photovoltaic cells generally depend on two parameters, namely the irradiance and the range of the temperature. This is the reason why the values of current and the operating voltage is continuously required to be varied as per the weather conditions. The tracking of the highest power point along the voltage current (IV) curve of a photovoltaic cell is a complicated task. A PID controller is usually employed to perform the task of maintaining the stable value of current and voltage by evaluating the MPPT, thereby giving a constant value of current and voltage for every change in weather.

- Most power converters use PID controllers to regulate the charging and discharging of the capacitors and the firing of Insulated-Gate Bipolar Transistors (IGBTs) or similar electronic switches.
- Various research, development, and testing organizations such as chemical, pharmaceutical, and manufacturing industries make use of the PID controllers to maintain the humidity and temperature of a particular area at a constant level.

Looking into the uses of this control technology to manage parameters of systems provides an in-depth view of the controller applications to better evaluate their potential impact to grid energy management. These controllers are generally not expensive, require little training to use, require little maintenance, and process data independently. However, PID controllers have some limitations to their applications in managing all the parameters previously discussed at once.

The fundamental difficulty with PID control is that it is a feedback system, with constant parameters, needs occasional retuning, no direct knowledge of the process, and thus overall performance is reactive and results in a compromise.

3.1. Limitations of PID Controllers

Specific limitations or disadvantages of a PID controller include:

- PID controllers can be unstable if they are not calibrated and tuned properly.
- These types of controllers are susceptible to derivative noise amplification.
- The controller may sustain oscillations around the operating point and cause problems for the grid.
- The continuous variation in the load tends to affect the dynamic performance of the system, hence it might not be safe to use the controllers on complex electric grid coordination.
- Repeated tuning of the controller may reduce the life span and cause wear and tear.

3.2. Neuro-Fuzzy Logic Advantages

Neural network technology is applied in various fields such as in financial services, forecasting, marketing research, fraud detection, and risk assessment to name a few. They also provide the best solutions in problems like image recognition, speech recognition, and natural language processing. Due to the benefits of neural networks in various fields, it has become somewhat of a household name. However, every technology comes with its promises and its limitations. Below are some pros and cons of Neural Networks:

- *Data*: One of the things that increased the popularity of the neural network utilizing fuzzy logic techniques are that it can process large amounts of data. Neural networks can be more accurate when they receive more data and information whereas traditional control algorithms will reach a level, where more data doesn’t improve the performance.
- *Algorithms and High Computational Power*: Neural networks are becoming popular due to the advancement made in their algorithms themselves. These recent breakthroughs in the development of algorithms are mostly due to higher complexity with higher efficiency, making them run much faster than before, which makes it possible to process more data in the same period of time.
- *Incomplete Information*: The data may generate performance after Artificial Neural Network (ANN) training even with incomplete information. The performance loss in this scenario relies on the significance of the missing data.
- *Fault Tolerance*: Corruption of one or more cells of ANN does not prevent it from generating effective outputs. This feature makes the systems more fault tolerant and less susceptible to missing information or outliers.
- *Dynamic Functionality*: Neural networks are good to model nonlinear data sets with many inputs; for example, images. It is reliable in an application of tasks involving many features. It works by splitting the problem of classification and processing of data into a layered network of simpler elements [5].
- *Parallel Processing Ability*: ANNs have numerical strength that can perform more than one job at the same time.

3.3. Neuro-Fuzzy Logic Challenges

Neuro-fuzzy logic computational methods possess valid advantages that could be utilized for large scale energy management, but as with any system there are challenges that must be recognized in order to be mitigated in application. The primary disadvantages are listed below:

- *Black Box*: One of the most distinguishing disadvantages of the neural network is their ‘’black box” nature. It means that we don’t know how and why the neural network came up with a certain output. For instance, when you put an apple’s picture into a neural network and predict it’s a cat, it’s very difficult to comprehend what led to this resulting forecast. When you have human interpretable characteristics, understanding the cause of your error is much simpler. In comparison, algorithms like decision trees are very interpretable. This is important, because in some domain’s interpretability is critically important [4].
- *Amount of Data*: Neural networks require much more data than many other traditional algorithms, where it is preferred to train the system using thousands if not millions of quality samples. For energy management, this data availability is not an

issue. In most applications this is a serious problem, and many neural network problems can be solved using fewer data than many other algorithms. This leads to the problem of over-fitting and generalization. The mode relies more on the training data and may be tuned to the data.

- *Computationally Expensive*: Neural networks are more computationally expensive than many other traditional algorithms. Most of the traditional algorithms take much less time to train, ranging from a few minutes to a few hours or days [4].
- *Determining Network Structure*: There is no specific rule for determining the structure of a neural network. The appropriate network structure is achieved through experience combined with trial and error in order to best design a system that understands the processes.
- *Unknown Network Duration*: Reducing the network to a certain value of the sampling error implies that the training must be complete. This value does not always offer the best outcomes [4].

4. Approach

Neuro fuzzy logic as a programming method is a rather young method of artificial intelligence. This method begins with the machine learning concepts of McCullough and Pitts who developed the neural network process in 1943 [6,7]. The timeline of these developments of neural networks and fuzzy logic can be seen in Table 1. As the years went by, other researchers gained interest and built their findings to develop more powerful neural network operations. Fuzzy logic was developed several decades later in 1964 by Zadeh, and research continued that blended the two concepts of data evaluation to become known as neuro fuzzy logic [7,8]. In essence, this topic combines the computational methods of processing large data sets in fuzzy logic with the ability of artificial learning within neural networks to develop into the current concept of deep learning coined by Hinton in 2012 [7,19]. In this manner, the idea is that the electric grid could make creatively complex decisions to common or critical issues, which would ultimately support a reliable and more efficient electric grid.

Table 1. Timeline of Artificial Learning [7]

Timeline of Artificial Learning		
Year	***Author***	***Concept***
1943	McCullough & Pitts [6]	Perceptron network with two artificial neutrons
1949	Hebb [9]	Hebbian learning rule
1958	Rosenblatt [10,11]	Perceptron network models
1960	Widrow & Hoff [12]	Adaline neural network
1962	Widrow [13]	Madaline neural network
1964	Zadeh [8]	Fuzzy logic
1982	Hopfield [14]	Hopfield network
1986	Rumelhart et al. [15]	Backpropagation neural network
1988	Chang & Yang [16]	Cellular neural network
1995	Cortez & Vapnik [17]	Support vector machine
2002	Gerstner & Kistler [18]	Spiking neural network
2012	Hinton [19]	Deep learning neural network

4.1. Opportunities

The concept here is to harness the advantages of both neural networks and fuzzy logic to improve the current grid management techniques. Fuzzy logic is a method of reasoning that is like how humans make decisions, whereas neural networks are thinking processes that mimic neuron functionality in the brain [20]. Neural networks bring a method to process data in a decision-making framework and fuzzy logic brings the ability to process and learn from large data sets through mathematical computational relationships between data points. Neural networks allow us to replicate the processing ability or learning ability of the human brain. Fuzzy logic allows us to develop methods to increase the amount of data processed utilizing matrices and associated operators. Fuzzy logic brings the ability to discern decisions from large data sets that are related or unrelated in nature [20]. When coupled together, these systems can process large data sets, learn from them, and become more effective at making appropriate decisions over time. Based upon human physiology of the brain, we can only receive between 5-9 inputs to decide effectively [21]. When the power of neural networks is combined with fuzzy logic, the number of inputs becomes limitless but exponentially compounding [22]. In essence, this would be bringing much more computational power to any decision-making scenario such as the grid. In this method, we are exponentially more capable at making complex decisions than a human or one method alone.

4.2. Neuro-Fuzzy Network Capabilities

The combination of neural networks and fuzzy logic gives energy management decision making software the ability to make decisions like that of a human but with many more inputs and computational accuracy. This amount of data processing power along with machine learning, will allow the grid to make decisions that effectively humans cannot. The grid is an increasingly complex system on interconnected generators, consumers, and mitigators. One that is gaining complexity at a seemingly exponential rate, which creates an opportunity for management systems to be developed and deployed to solve modern problems. These complex energy management challenges are the result of managing many systems consisting of different production patterns, usage patterns, generator types of varying power factor and response times, etc. The current grid energy management methods used take into consideration load flow and power quality to ensure sufficient power supply needs are met, but fuzzy logic may be able to manage this more effectively.

According to Hinton, the accredited founder of modern deep learning using neural networks, these applications bring the capability for computers to process decisions like the human brain with unlimited inputs [23]. This amount of efficient processing power can allow a grid energy management system to make better decisions than a human could in the same environment. The idea is that these decisions, or rather real time solutions, could result in more creative and innovative energy management decisions to be made.

4.3. Neuro-Fuzzy Network Concept

Artificial intelligence seeks to replicate human intelligence and by nature allows us to apply this to the grid to bring more complex decision-making ability to how it is managed.

As a thought experiment, imagine the current system that can evaluate the movement of load within a substation. In a simple form, a substation in essence is evaluating the measured outputs and comparing it to available inputs to be able to meet required load demanded by consumers on the distribution system. In the meantime, this system is also evaluating the quality of power it is delivering to continuously adjust leading or lagging voltage or current as well as other inefficiencies in the system to ensure high quality usable energy to end users. A neuro fuzzy logic-based system could allow many substations to communicate with one another. In one extreme scenario utilizing current viewpoints, the problem locally may make the determination that there isn't enough available energy to serve a localized load which would result in either power quality problems or blackouts. A neuro fuzzy logic-based system could utilize the regional transmission network to potentially balance the transmission grid to satisfy distribution demands through the macroscopic movement of energy. In this manner, the current method of managing energy is made based upon sensor input and either simple program or human interpretation of readings of immediate data availability, whereas a more robust program could process traditionally unforeseen solutions outside of the local perspective. This aspect would bring a more efficient systems engineering approach to managing one of the largest and most complex machines in the world [24].

5. Application

Compared to traditional analog computational processing, neuro-fuzzy logic allows the same equipment to process more data faster than the analog and other programming methods [25]. Quantifying how much more data can be processed is difficult to determine given that there are still programming techniques being developed for artificial intelligence processing and software architecture varies due to programmer methods. Nonetheless, the application of neuro-fuzzy logic for decision making in grid energy management remains an opportunity for grid operators to take advantage of. The amount of processing and decision-making ability that neural networks combined with fuzzy logic techniques is not only higher than current practices but allows the system to make decisions previously unavailable. This ability to make new, unique, and creative decisions in complex grid scenarios is due to the ability for neuro-fuzzy logic to identify relationships in seemingly unrelated data. When coupled with the ability for neural networks to adjust according to current trends, this makes its application as an active, effective, efficient, and reliable grid energy management tool to ensure energy safety and security.

Current methods of grid control typically consist of separate networks of distribution, transmission, and sub-transmission, respectively. In general, electric energy reaches the customer from large, centralized generation plants travelling miles to a substation where it decreases in voltage and ultimately to a transformer once it reaches the end user. These separate networks each operate at a different voltage, otherwise known as the potential difference in a conductor, which allows a specific conductor to move varying amounts of energy through the same size conductor within its thermal ratings. These independently operating networks present an opportunity and a need for neuro-fuzzy logic systems that will be discussed in later sections. For example, if the local independent, equal-voltage networks only communicated with themselves, then there is no "grid" efficiency to resolving complex supply issues, capacity constraints, or another load scenario. This linkage between equal-voltage networks will open power flow and energy supply solutions that wouldn't have been found previously.

Neuro-fuzzy logic applications are not limited to grid integration alone but also have other areas of application such as:

- Aerospace: Aircraft component fault detectors and simulations, aircraft control systems, high-performance auto-piloting, and flight path simulations
- Automotive: Improved guidance systems, development of power trains, virtual sensors, and warranty activity analyzers
- Electronics: Chip failure analysis, circuit chip layouts, machine vision, non-linear modeling, prediction of the code sequence, process control, and voice synthesis
- Manufacturing: Chemical product design analysis, dynamic modeling of chemical process systems, process control, process and machine diagnosis, product design and analysis, paper quality prediction, project bidding, planning and management, quality analysis of computer chips, visual quality inspection systems, and welding quality analysis
- Mechanics: Condition monitoring, systems modeling, and control
- Robotics: Forklift robots, manipulator controllers, trajectory control, and vision systems
- Telecommunications: ATM network control, automated information services, customer payment processing systems, data compression, equalizers, fault management, handwriting recognition, network design, management, routing and control, network monitoring, real-time translation of spoken language, and pattern recognition (faces, objects, fingerprints, semantic parsing, spell check, signal processing, and speech recognition)

5.1. Distribution

The electric grid typically consists of an interconnected system of consumers, power distribution, power transmission, and generation resources [26]. The distribution system in the United States operates on voltages commonly from 15 – 34.5 kV, whereas consumers utilize the electric energy at voltages from 120 – 480 V [26]. The distribution system operates on the low-voltage/secondary (commonly known as the "low-side") of the substation and distributes power with one point of conversion (transformer) between the utility and the consumer. These points of *delivery* between the utility and the consumer are commonly at metering points and referred to as "points of common coupling" [27]. The methods that these occur are typically via pass-through meters or utilizing current transformers and operate on the consumers voltage range. These metering points provide the opportunity to measure and collect valuable consumption data that can be utilized to make grid-wide decisions.

Distribution grids are commonly viewed as independent operating systems with "one input" and "many outputs". The single input is viewed as the connection point of primary side of the substation, which is the transmission system or the supply side from the perspective of the distribution utility. The "many outputs" are the consumers' meters. The data points along this path are the substation secondary bus, distribution circuit breakers, critical points along the feeder, and customer metering locations. The most valuable data collected along these points are related to power flow such current, load, and energy, whereas power quality is also important for measuring voltage, phasing, cycles, and ultimately power factor. In conclusion, these data points offer valuable insight into predicting future energy demand patterns as well as planning future infrastructure improvements.

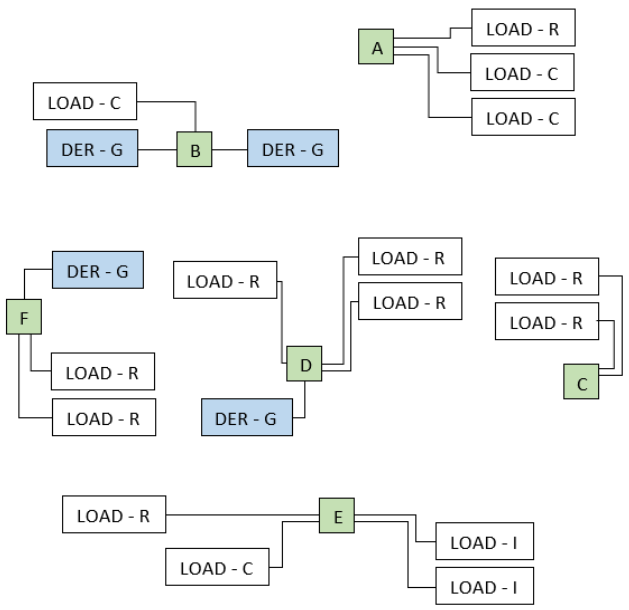


Figure 5. Illustration is a representation of a simple distribution grid indicated in a one-line diagram style showing substations A,B,C,D,E, and F with varying distribution circuits with either DER-G (DER generation source) and combinations of Load R (residential load), C (commercial load), and I (industrial load)

5.2. Transmission

The United States transmission grid consists of interconnected networks transmitting electric energy many miles. These high voltage networks operate at 69kV or greater and are meant for moving large amounts of energy efficiently over long distances [26]. These systems, like distribution networks, measure both the power quality and load flow among the system. Like distribution systems, in this network the "customers" are substations, and the "inputs" are large, centralized power generation resources. This description tends to follow the ideals of a one directional flow of power, whereas substations can have bi-directional power flow capabilities. In either manner, substations are the net-load of the lower voltage systems fed by it that are either net-exporters or importers of electric energy. In that way, substations are viewed as net load centers as seen in Figure 6. Data from each substation and large generating plant assists regional transmission operators in ensuring reliable power flow, but they cannot access distribution resources in resolving electric grid reliability.

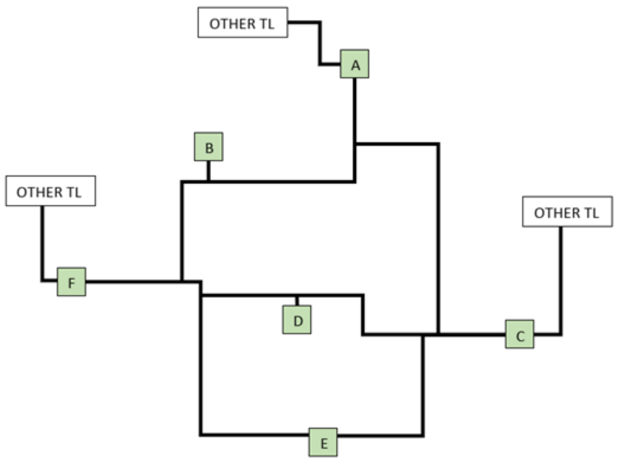


Figure 6. Illustration is a representation of a simple transmission grid indicated in a one-line diagram style showing substations A,B,C,D,E, and F interconnected with a regional sub-transmission network, with three external transmission feeds from other power generation resources labeled with "OTHER TL"

5.3. Combined Network Model

As discussed in the previous two sections, the distribution and transmission system monitoring and operations systems do not make decisions on the other groups data but rather the summary or net-data provided. The distribution system can only interact with and monitor consumers (meters) and generators (DERs) when making power flow decisions. This is the same scenario with the transmission system. Each one operates independently with little access to resources within the other network. Figure 7 represents a combined perspective of an integrated distribution and transmission system. From the perspective of the monitoring and decision system, it would have access to both distribution and transmission data. This provides the energy management system with access to more data and control over the reactive and proactive infrastructure resources. If the macroscopic electric grid could possess a larger perspective of status, need, and opportunity, then it could make more efficient and cost-effective decisions regarding power flow and quality.

An interconnected and communicating regional distribution and transmission system is shown in Figure 8 from the perspective of the management system. The system consists of location, capacity, equipment, consumption, and quality data of critical nodes along the network as previously discussed. When reliability is being measured amongst the system, Figure 8 illustrates a common concern that occurs in extreme high load scenarios. In this scenario, Substation E is experiencing high load with low supply immediately available to the substation as resource. In a world where neuro-fuzzy logic was implemented to connect these separate networks and resources together to improve network operability, the system would be able to recognize that within close proximity were four DERs that the system could ramp as response to this event. This example is for illustrative purposes only, but DERs exist in many forms and not only as a generation resources. This system would effectively be capable of controlling generation and load shedding resources in order to balance these events. Rather than curtailing available power to customers resulting in intermittent blackouts, the system is able to ramp up available DER generation sources, and/or battery storage sources, on Substations B, D, and F to assist in offsetting demand on Substation E.

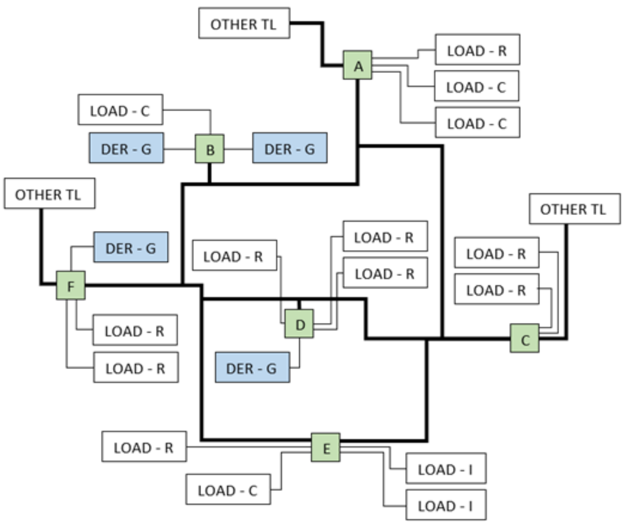
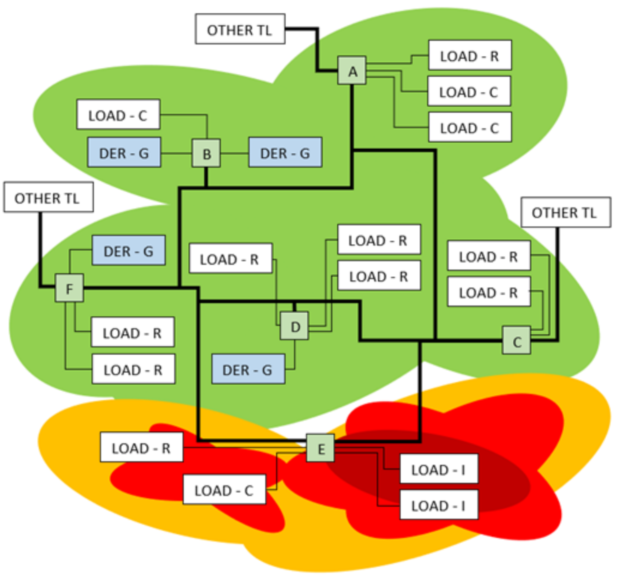


Figure 7. Illustration is a representation of the combination of Figures V and VI of a one-line diagram style showing substations A,B,C,D,E, and F with varying distribution circuits with either DER-G (DER generation source) and combinations of Load R (residential load), C (commercial load), and I (industrial load).



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6. Discussion

The application of neuro-fuzzy logic in grid energy management has many possibilities to contribute to the efficiency of the current electric grid operations. Through this method, the electric grid has the possibility to make available previously unrecognized potential in the grid's operations such as capacity, DER integration, and interoperability.

6.1. Grid Management

It is evident that the application of neuro fuzzy logic contributes to providing creative solutions previously not available when resolving power flow or quality issues. When evaluating the problem in this manner there are many more resources available to provide distribution system assistance in a scenario where it is needed. This is due to simply being available to the system as both a data input but also a resource. The purpose of this is to allow the system to have access to more resources via the merging of the distribution and transmission systems' operations management system when responding to system events. To maintain the delivery of energy to consumers, creative solutions are required to avoid the disruption of power to consumers. As an example, one solution to the issue illustrated in Figure 8 is to ramp some DER resources, including battery storage units, to make available additional transmission capacity to Substation E. In some jurisdictions, the systems could have access to curtail consumer demand through a direct load control style of voluntary program to make available additional capacity as needed. Fuzzy logic and neural networks would only contribute to the decision-making process while taking these resources into consideration. The result is like empowering an employee to decide, because ideally, they'll make the decision that they have the most control over. If they're made available to additional resources under their control, then they'll take advantage of them.

6.2. Distribution Planning

In the United States and around the world, DERs are becoming increasingly popular for many reasons, and thus creates a more decentralized electric grid. Rather than the traditional one-way flow of energy, it is now exponentially more complex as any substation or circuit could be moving power bidirectionally. A relevant topic in the United States in recent years (2020-2023) has been the need for expedited review processes related to DER development. Historically, this process has been slow and riddled with surprises for third parties, and there is currently planning underway to develop a modeling method that clusters DERs during evaluation [28]. Fuzzy logic utilizes functions to cluster and group similar variables, in this case projects, to evaluate specific parameters internally or externally. This ability would allow the appropriate entities the option to evaluate groups of projects at one time to evaluate grid operational concerns. In return, this would improve the rate of DER implementation, and since the majority of DERs are renewable energy, it would thus reduce the impact of carbon emissions. In this manner, the use of neuro-fuzzy logic for clustered interconnection evaluations would be in the public interest due to carbon emission reduction, renewable energy implementation, and increased grid reliability.

6.3. Neuro-Fuzzy Logic

The power of neural networks is the ability to process data and learn from that data. Fuzzy logic adds the ability to process and manipulate large data sets to make and implement decision and controls. When combined, these make a system growing in increased complexity easier to manage and to take more advantage of current infrastructure for both operational and planning processes.

Neuro-fuzzy logic attributes that make it a good candidate for grid energy management controls and decision making are the following: 1) number of inputs, 2) variable relationships, 3) learning capability, 4) data clustering, 5) decision making, and 6) pattern recognition. This processing methodology uses matrices to process and manipulate large data sets efficiently. In the example shown in Figure 8, the system could be primarily measuring load values combined with available load response resources to determine a new power flow that resolves the critical load event. To accomplish power flow, the management system would need access to information noting which component are directly related. For example, from Figure 8, Substations F, D, and C are directly related or connected to Substation E where the critical load event has occurred. If the system responds then it needs to know the proximity and connectivity of the resources to Substation E. This type of problem, balancing the grid or grid response, is a good application opportunity for this type of energy management. Those relational aspects are easily accomplished through neural networks which can be used to establish related components on the grid and their capacities. Khonen's Learning Rule is a potential application to resolving regional reliability issues, because it allows for clustering of data and the modification of groups of data [29,30]. In the scenario discussed in the example, Khonen's Learning Rule could utilize DER resources across the local network to ramp up to meet the localized need [30].

7. Conclusion

There is no question that neuro-fuzzy logic could bring unique approaches to resolving grid energy management issues. The benefits that neuro-fuzzy logic brings are as previously mentioned the following: 1) number of inputs, 2) variable relationships, 3) learning capability, 4) data clustering, 5) decision making, and 5) pattern recognition. These advantages will allow the grid to operate more efficiently and reliably by having a more advanced grid energy management system coordinating more creative responses to grid issues. It is possible, that through accessing the networks' resources including DERs that this methodology could yield additional underutilized capacity. This would directly and indirectly contribute to reliability, efficiency, and affordability. Additional benefits could see carbon emission reduction through the increased adoption of DERs which is currently led by renewable energy technology [31]. All of this coupled together increases the energy security for countries that utilize it, and in this case explicitly the United States.

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References

[1] U.S. Department of Energy. (n.d.). *About Us: Department of Energy*. https://www.energy.gov/about-us#:~:text=The%20mission%20of%20the%20Energy,Learn%20more.

[2] Fathy A, Kassem AM. Antlion optimizer-ANFIS load frequency control for multi-interconnected plants comprising photovoltaic and wind turbine. ISA Trans 2019; 87: 282-96 Antlion optimizer-ANFIS load frequency control for multi-interconnected plants comprising photovoltaic and wind turbine – ScienceDirect.

[3] Eshetu W, Sharma P, Sharma C. ANFIS based load frequency control an isolated micro grid. In: 2018 IEEE International Conference on Industrial Technology (ICIT), Lyon; 2018. p. 1165-70.

[4] Limitation of PID controllers https://www.academia.edu/37038423/LIMITATIONS_OF_PID_CONTROLLERS.

[5] Prasanna Shrestha, Future Tech, August 27,2019The Advantages and disadvantages of Neural Networks, https://gkstuffs.com/future-tech/advantages-and-disadvantages-of-neural-networks/.

[6] W. McCulloch and W. Pitts, "A logical calculus of the ideas immanent in nervous activity," Bulltin of Mathematical Biophysics, vol. 7, pp. 115-133, 1943.

[7] Madhiarasan, M. & Louzazni, M. (April 18, 2022). *Analysis of Artificial Neural Network: Architecture, Types, and Forecasting Applications*. Hindawi: Journal of Electrical and Computer Engineering. https://downloads.hindawi.com/journals/jece/2022/5416722.pdf.

[8] L. A. Zadeh, "Fuzzy sets," Information and Control, vol. 8, pp. 338-353, 1965.

[9] D. O. Hebb, 1e Organization of Behavior, Wiley & Sons, New York, NY, USA, 1949.

[10] F. Rosenblatt, "+e Perceptron — a perceiving and recognizing automaton," Report 85–460–1, Cornell Aeronautical Laboratory, New York, NY, USA, 1957.

[11] F. Rosenblatt, Principles of Neurodynamics, Spartan Books, Washington, DC, USA, 1962.

[12] B. Widrow and M. E. Hoff, "Adaptive switching circuits," 1960 IRE WESCON Convention Record, pp. 96-104, 1960.

[13] B. Widrow, "Generalization and information storage in networks of Adaline' neurons," in Self-Organizing Systems 1962, M. C. Yovitz, G. T. Jacobi, and G. Goldstein, Eds., Article ID 435461, Spartan Books, Washington, DC, USA, 1962.

[14] J. J. Hopfield, "Neural networks and physical systems with emergent collective computational abilities," Proceedings of the National Academy of Sciences of the USA, vol. 79, no. 8, pp. 2554-2558, 1982.

[15] D. E. Rumelhart, G. R. Hinton, and R. J. Williams, "Learning internal representations by error propagation," in PDP Research Group, Parallel Distributed Processing: Explorations in the Microstructure of Cognition (V1 and V2), D. E. Rumulhart and J. L. McClelland, Eds., vol. 1, MIT Press, Cambridge, MA, USA.

[16] L. O. Chua and L. Yang, "Cellular neural networks: theory," IEEE Transactions on Circuits and Systems, vol. 35, pp. 1257-1272, 1988.

[17] C. Cortes and V. N. Vapnik, "Support-vector networks," Machine Learning, vol. 20, no. 3, pp. 273-297, 1995.

[18] W. Gerstner and W. M. Kistler, Spiking Neuron Models: Single Neurons, Populations, Plasticity", Cambridge University Press, Cambridge, MA, 2002.

[19] G. E. Hinton, "A practical guide to training restricted Boltzmann machines," in Neural Networks: Tricks of the Trade, G. Montavon, G. B. Orr, and K. R. M¨uller, Eds., vol. 7700, Springer, Berlin, Germany, 2012.

[20] Lithmee. (August 14, 2019). *What is the Difference Between Fuzzy Logic and Neural Network*. Peddia.com. https://pediaa.com/what-is-the-difference-between-fuzzy-logic-and-neural-network/#: ~:text=The%20main%20difference%20between%20fuzzy,human%20brain%20to%20perform%20computations.

[21] Encyclopaedia Britannica. (n.d.). *Physiology*. https://www.britannica.com/science/information-theory/Physiology.

[22] Dintsis, Danil. (2014). Re: What is the maximum number of variables that can be handled by fuzzy inference system? Retrieved from: https://www.researchgate.net/post/What_is_the_maximum_number_of_variables_that_can_be_handled_by_fuzzy_inference_system/5461ea41cf57d72b058b461d/citation/download.

[23] Comparison of fuzzy PID controller with conventional PID controller in controlling the speed of brushless DC Motor, S. sunsith, Lizi Joseph, M. Saritha http://www.ieejournal.com.

[24] Goldthau, A. (2017). *The handbook of global energy policy*. Wiley Blackwell. https://www.quantamagazine.org/artificial-neural-nets-finally-yield-clues-to-how-brains-learn-20210218/.

[25] Eibagi, A. (2014). *Big Data Analysis Using Neuro-Fuzzy System*. San Jose State University. https://scholarworks.sjsu.edu/cgi/viewcontent.cgi?article=1367&context=etd_projects.

[26] Gilstrap, M., Amin, S., & Decorla-Souza, K. (July 2015). *United States Electricity Industry Primer*. U.S. Department of Energy: Office of Electricity Delivery and Energy Reliability. https://www.energy.gov/sites/prod/files/2015/12/f28/united-states-electricity-industry-primer.pdf.

[27] Hansen, D. (July 24, 2008). *IEEE 519 misapplications— Point of common coupling issues*. IEEE. https://ieeexplore.ieee.org/document/4596868.

[28] Richmond-Crosset, K. & Greene, Z. (September 30, 2022). *How Distributed Energy Resources Can Lower Power Bills, Raise Revenue in US Communities*. World Resources Institute. https://www.wri.org/insights/distributed-energy-resources-explained-us.

[29] B. Ruprecht et al., "Possibilistic Clustering Enabled Neuro Fuzzy Logic," 2020 IEEE International Conference on Fuzzy Systems (FUZZ-IEEE), 2020, pp. 1-8.

[30] Curry, Bruce and Peter H. Morgan. "Evaluating Kohonen's learning rule: An approach through genetic algorithms." Eur. J. Oper. Res. 154 (2004): 191-205.

[31] Center for Climate and Energy Solutions. (n.d.). *Renewable Energy*. https://www.c2es.org/content/renewable-energy/.

[32] Thangaramya, K., Kulothungan, K., Logambigai, R., Selvi, M., Ganapathy, S., & Kannan, A. (January 28, 2019). *Energy aware cluster and neuro-fuzzy based routing algorithm for wireless sensor networks in IoT*. Elsevier: Computer Networks. https://www.sciencedirect.com/science/article/abs/pii/S1389128618307771.

[33] Ananthaswamy, A. (February 18, 2021). Artificial Neural Nets Finally Yield Clues to How Brains Learn. Quanta Magazine.

[34] British Broadcasting Corporation. (n.d.). *Electric circuits – AQA*. https://www.bbc.co.uk/bitesize/guides/zgvq4qt/revision/3#:~:text=Potential%20difference%20is%20a%20measure,two%20points%20in%20a%20circuit.

[35] Nazar AA, Jayabharath R, Udayakumar MD. An ANFIS based advanced MPPT control of a wind-solar hybrid power generation system. IREMOS 2014; 7: 638.

[36] Real-life and business Application of Neural Networks. Real-Life Applications of Neural Networks | Smartsheet.