Artificial Intelligence and the Nanogrid in Critical Facility Power Infrastructure

A technical paper prepared for presentation at SCTE TechExpo24

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1. Introduction

Artificial Intelligence (AI) refers to developing computer systems that can perform tasks typically requiring human intelligence. These systems learn from data, adapt to new information, and make decisions based on patterns and algorithms. Nanogrids are localized energy systems that operate independently or in conjunction with the main power grid. Unlike large-scale grids, nanogrids serve specific areas, buildings, or communities. They integrate various Distributed Energy Resources (DERs), such as generators, solar panels, wind turbines, batteries, and fuel cells. Using predictive analytics and optimization, we can combine AI and critical power infrastructure to produce a more resilient, sustainable, and efficient system at a lower cost. We are nearing the point where distributed generation becomes the least costly way to provide electricity. The declining cost of renewables and technological advancements make this shift possible.

2. Nanogrid Architecture for Resiliency

In the SCTE Expo 2023, we proposed the architecture for high reliability and resiliency, as shown in Figure 1 [1]. To recall the paper's summary, the proposed architecture addresses two critical reliability concerns: the single point of failure of ATS and HVAC loads on backup power.

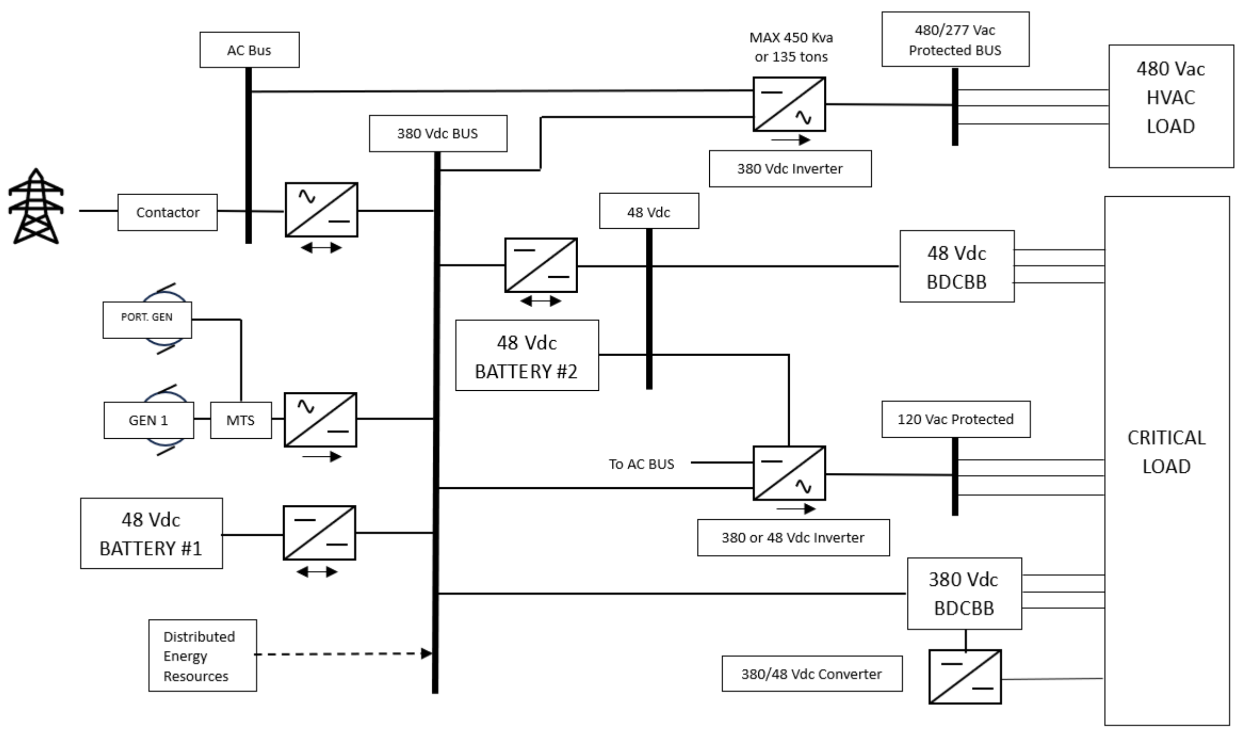

Figure 1: Proposed nanogrid architecture

The essential DC bus integrates distributed energy resources and enables power flow to various loads with distributed architecture. The logical step from power architecture is monitoring and controlling the capabilities of the proposed architecture. In the next sections of this paper, we will discuss the communications flow between distributed power conversion stages and energy resources.

Power conversion and distribution will have a local system controller to maintain a resilient architecture. Using linear control methodologies, the system controller monitors and controls the power flow through standard feedback mechanisms.

Modern optimization techniques, such as machine learning and reinforcement learning, can be applied to realize the full potential of distributed architectures. This can be achieved through the distributed communications architecture.

The SCTE Microgrid working group is working toward AI management of a critical facility. The diagram below shows a basic thought pattern for achieving this goal.

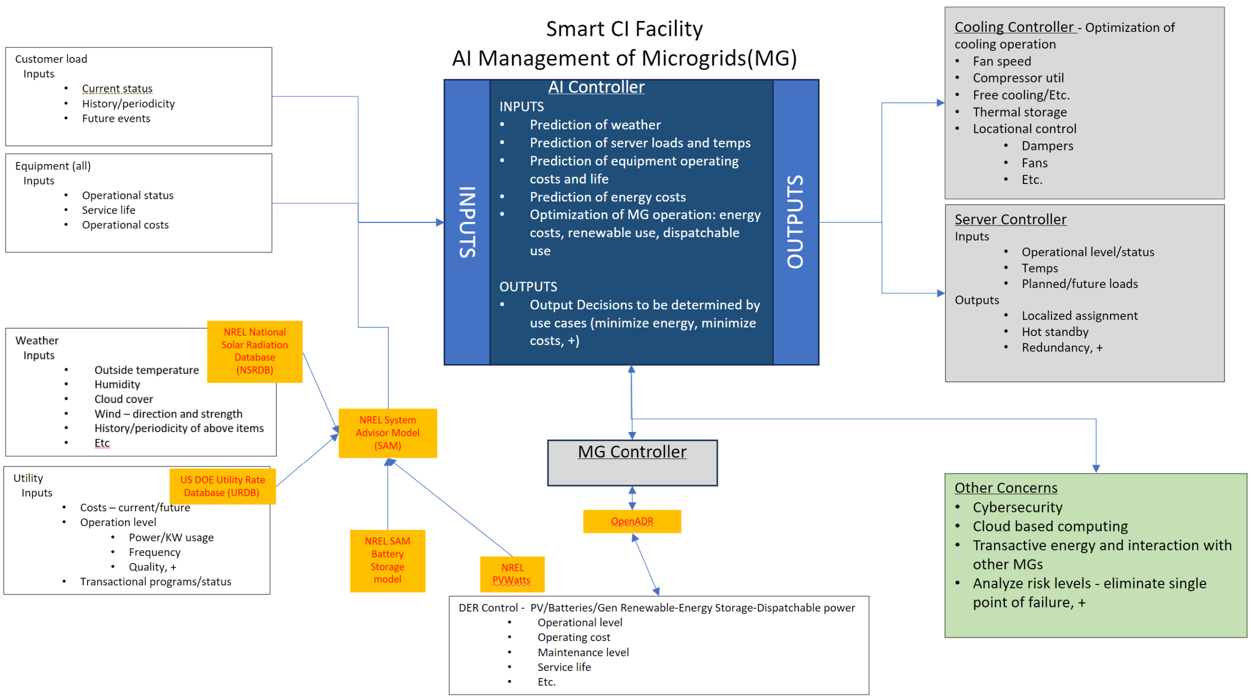

Figure 2: Microgrid architecture thought pattern. Diagram courtesy of Comcast, Mike Nispel.

3. Artificial Intelligence

AI is today's buzzword. It is the way of the future. How can we use this resource? AI refers to using technologies that enable machines and computers to mimic cognitive functions associated with human intelligence. AI encompasses a broad field of technologies implemented in systems to reason, learn, and act.

3.1. Machine Learning (ML)

While AI is the broader concept, ML is an application of AI. ML is a subset of AI that allows machines to learn and improve from experience without explicit programming. This process uses algorithms to analyze data and learn from insights and improves performance over time as it’s exposed to more data. Examples of ML are Intelligent networks and network optimization, predictive maintenance, business process automation, upgrade planning, and capacity forecasting. Machine learning algorithms improve performance over time as they are trained—exposed to more data. Machine learning models are the output, or what the program learns from running an algorithm on training data. The more data used, the better the model will get.

Machine learning (ML) techniques can be used to control and optimize DC power systems in several ways [2] [3]:

Performance Improvement: ML techniques have been applied to power electronics control and optimization to improve the performance of power electronics systems. These techniques can reduce the computational expense of characterizing DC-DC converters, which is necessary for designing and optimizing power electronics systems.

Predictive Modeling: Machine learning techniques such as support vector regression and artificial neural networks have been utilized to predict DC-DC converters' performance accurately. This can help control the power flow and improve the system's efficiency.

Fault Diagnosis and Condition Monitoring: ML techniques, especially classification or regression techniques, have also been used in condition monitoring and fault diagnosis on various electric machines. This can help in the early detection of faults and prevent system failures.

Optimization: Advances in processing power and monitoring capabilities create a significant opportunity for machine learning to guide best practices and improve DC efficiency.

Real-Time Implementation: Some research has focused on real-time implementation of DC/DC power converter control-based deep machine learning techniques.

Machine learning can significantly impact DC power control by enhancing performance, enabling predictive modeling, assisting in fault diagnosis, optimizing data centers, and facilitating real-time implementation.

3.2. Real-Time Monitoring.

Real-Time Monitoring "Sensors" read actual, present conditions, such as electrical current, voltage, temperature, etc. These points are monitored to collect trending data for capacity and growth and to maintain / not exceed manufacture design parameters. This data will be analyzed for equipment load management, load trending, and forecasting equipment replacement. Machine learning will use This data to facilitate the decision tree within the software.

Data sets for monitoring site conditions have grown to the point where they are no longer manageable due to the sheer size and complexity of the systems they are trying to manage. A typical site may have more than 1500 points or more that need to be monitored. We have provided a list of generic points that may be monitored within facilities. The ML would use this data to understand the site's "real-time" condition.

Table 1: Typical equipment and sensors in critical facilities

Equipment Classification	Function	Type	Classification - Sensor, Critical or Information	Description
Facility Power:				
Utility Voltage	real-time	analog	Sensor	Utility Power Voltage Reading - Line to Line or Line to Neutral

Facility Ground Current	real-time	analog	Sensor	Facility ground current
Voltage (ATS load side)	real-time	analog	Sensor	Voltage on output (load side) of ATS - per phase
Amps (ATS load side)	real-time	analog	Sensor	Current on output (Load side) of ATS - per phase
GFI Trip	alarm	binary	Critical	Ground fault interrupter has operated - open circuit
AC Fail	alarm	binary	Critical	Loss of utility power and phase loss
Low Voltage DC	alarm	binary	Critical	DC battery plant discharge low voltage limit
Very Low Voltage DC	alarm	binary	Critical	DC battery plant discharge (critical) very low voltage limit (near shutdown stage)
Battery Plant on Discharge	alarm	binary	Critical	No AC power to rectifiers
TVSS:				
Active Alarm or Fault	alarm	binary	Critical	Unit has failed
Generator:				
Battery Start Voltage	real-time	analog	Sensor	Generator - engine start battery voltage reading
Fuel Tank Level	real-time	analog	Sensor	Fuel tank level reading
Low Fuel Level 35%	alarm	binary	Critical	Fuel tank 35% remaining in tank set point
Fuel Tank Leak Detect	alarm	binary	Information	Fuel tank leaking between inner and outer tank liner
Day Tank Pump Failure	alarm	binary	Critical	Day tank pump failure
Propane Fuel Source	alarm	binary	Information	Propane fuel source indicator - present or not
Switch to Propane / Natural Gas	alarm	binary	Information	Indicating which fuel source generator is running on
Not in "Automatic" / "Not Ready for service"	alarm	binary	Critical	Generator is in manual mode for starting
Generator Run	alarm	binary	Information	Indicator generator is running only
Generator EPO Operated	alarm	binary	Critical	Generator emergency shutdown switch has been operated (pushed)
Battery Charger Fail	alarm	binary	Critical	Engine start battery charger has stopped charging battery
High Coolant or Oil Temp	alarm	binary	Critical	Engine coolant or oil is exceeding mfg recommended operating temperature
Low Coolant Level	alarm	binary	Critical	Engine coolant is below mfg recommended level to run
Output Circuit Breaker Open	alarm	binary	Critical	Generator load circuit breaker is open - no output
Low Oil Pressure	alarm	binary	Critical	Engine oil level is below mfg recommended level
Over-crank	alarm	binary	Critical	Engine has exceeded the number of starter cranking cycles to start the engine
Engine Jacket Water Heater Failure	alarm	binary	Information	Engine coolant heater has failed
Redundant Generator Power Notification	alarm	binary	Information	Generator has switched to a secondary source
Summary Alarm	alarm	binary	Information	Composite alarm of all the NFPA 110 safety shutdowns
ATS:				
ATS Position N/ E	N/E	binary	Information	Transfer switch position - operated to normal or generator power
Not in "Automatic"	alarm	binary	Critical	Transfer switch is operating in manual mode only
Normal Mode Status	alarm	binary	Information	ATS working properly
Manual or Bypass Position	alarm	binary	Information	ATS on alternate source - generator
Bypass Position	alarm	binary	Information	ATS is in bypass mode
Alternate Source Power Available	alarm	binary	Information	Secondary source available (generator)
Preferred Source Power Available	alarm	binary	Information	Commercial power source available

Equipment Classification	Function	Type	Classification-Sensor, Critical or Information	Description
UPS:				
Battery Voltage, DCV	real-time	analog	Sensor	UPS battery string voltage

Voltage Input	real-time	analog	Sensor	UPS line input voltage - per phase
Voltage Output	real-time	analog	Sensor	UPS output voltage - per phase
Current Input	real-time	analog	Sensor	UPS input current reading - per phase
Current Output	real-time	analog	Sensor	UPS output current reading - per phase
Input Power	real-time	analog	Sensor	UPS input Watts per phase
Output Power	real-time	analog	Sensor	UPS output watts per phase
Input Frequency	real-time	analog	Sensor	UPS input frequency
Output Frequency	real-time	analog	Sensor	UPS output frequency
On Bypass Mode Notification	alarm	binary	Critical	UPS in bypass - on commercial power source
On Battery Power Alarm	alarm	binary	Critical	UPS is running on battery reserve only
Circuit Breaker Open	alarm	binary	Critical	UPS output circuit breaker is open
Normal Mode Notification	alarm	binary	Information	UPS working properly
Summary Alarm	alarm	binary	Critical	Composite alarms
PDU or Distribution Equipment:				
Major Alarm Notification	alarm	binary	Critical	Critical to the operation of the equipment (close to out of service)
Minor Alarm Notification	alarm	binary	Information	Concern alarms to operation - not out of service
Ground Fault Alarm	alarm	binary	Critical	Circuit breaker has tripped on a ground fault indication
EPO:				
Activated or Ready	alarm	binary	Critical	Computer room "Emergency OFF Power" switch operated- removes all power
DC Plant:				
Amperage Load	real-time	analog	Sensor	Total battery plant discharge current drain (load)
Float Voltage	real-time	analog	Sensor	Battery charging voltage
Battery Temperature Mid String	real-time	analog	Sensor	Battery temperature reading in the middle of the battery string
Battery String Mid String Voltage	real-time	analog	Sensor	Battery mid-string voltage - reads 1/2 of string for balance - check for open cells
Battery Remaining Run Time	real-time	analog	Sensor	Calculated discharge time before the battery reaches the end cell
Battery Discharge voltage	real-time	analog	Sensor	Reading battery voltage as battery is on discharge
Rectifier Failure	alarm	binary	Critical	Rectifier - no output current
Rectifier Overload	alarm	binary	Critical	Rectifier output greater than 110%
Low Battery DC voltage	alarm	binary	Critical	DC battery string voltage limits
Fuse / Circuit Breaker Trip	alarm	binary	Critical	DC circuit breaker or fuse (tripped or fuse blown)
Low Voltage DC	alarm	binary	Critical	DC battery plant discharge low voltage limit
Very Low Voltage DC	alarm	binary	Critical	DC battery plant discharge (critical) very low voltage limit (near shutdown stage)
Battery Plant on Discharge	alarm	binary	Critical	No AC power to rectifiers
Inverter Plant:				
Amperage load	real-time	analog	Sensor	Total inverter plant current drain (load)
Inverter Failure	alarm	binary	Critical	Inverter fail - no output
Circuit Breaker Open	alarm	binary	Information	Tripped circuit breaker
Low Input Voltage	alarm	binary	Critical	Low DC input voltage

Equipment Classification	Function	Type	Classification - Sensor, Critical or Information	Description
HVAC:				
Room Temp / Humid	real-time	analog	Sensor	Read actual room temperature and humidity
Over Temperature	alarm	binary	Critical	High temperature alarm setting

Fan Failure Alarm	alarm	binary	Information	HVAC fan failure
CRAC Failure	alarm	binary	Critical	No cooling output
CRAH Failure	alarm	binary	Critical	No cooling output
Dry Cooler (DX) Failure	alarm	binary	Critical	No cooling output
Chiller:				
Major and Minor Contacts	alarm	binary	Information	Collection of alarm
Pump Failure	alarm	binary	Critical	pump fails to operate
Fire Detection and Suppression:				
Active Fire Alarm	alarm	binary	Critical	Building detected a fire condition
Fire Panel Trouble	alarm	binary	Critical	Trouble within the system or panel
Fire Panel Supervisory	alarm	binary	Critical	System change of state
Water Leak Detection Circuit	alarm	binary	Critical	Pre-action fire system water leakage
Security/BMS:				
Associated Building Alarm	alarm	binary	Critical	Building security system failed
Open Door	alarm	binary	Information	Door open
Water Sensor	alarm	binary	Information	Water on floor
Tower Lighting:				
Light Failure	alarm	binary	Critical	Tower beacon light out

Growth in critical facilities equipment has resulted in growth in the origins of data sets. The equipment producing these data sets is modular. For example, the DC plant listed in **Error! Reference source not found.** includes voltages, currents, and temperatures from every modular power converter, battery, and additional sensor placed in power plants. Communication of this data from every component to the processing unit, either on-premises or remote private cloud, requires a lot of bandwidth and processing power. Hence, the paper proposes a layered data processing approach.

3.3. Random Forest

Random forest is a commonly used machine learning algorithm trademarked by Leo Breiman and Adele Cutler [4]. It combines the output of multiple decision trees to reach a single result. Its ease of use and flexibility have fueled its adoption, as it handles classification and regression problems. While we currently use reporting systems to monitor the system, we can utilize ML to change the operation of the systems based on the data. The volume of calculations facilitated with the ML decision tree allows the system to determine the next step accurately.

1. Step 1: Select random K data points from the training set.
2. Step 2: Build the decision trees associated with the selected data points (Subsets).
3. Step 3: Choose the number N for decision trees you want to build.
4. Step 4: Repeat Step 1 and 2.
5. Step 5: For new data points, find the predictions of each decision tree and assign the new data points to the category that wins the majority votes.

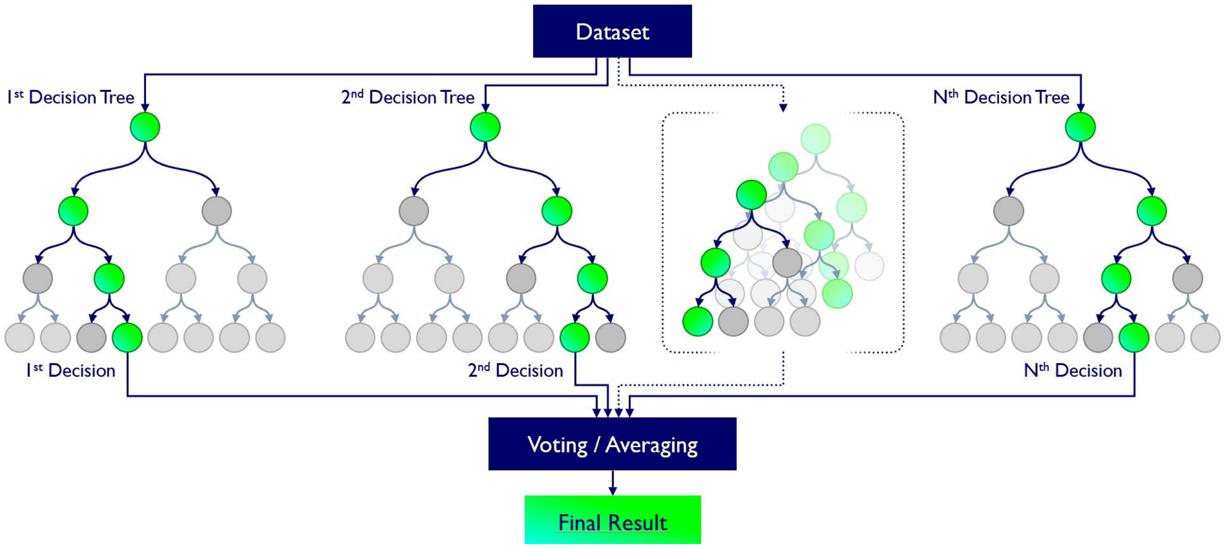

Figure 3: Decision tree for Random Forest

3.4. Key Features of Random Forest

Some of the Key Features of Random Forest are discussed below:

1. **High Predictive Accuracy:** Imagine Random Forest as a team of decision-making wizards. Each wizard (decision tree) looks at a part of the problem, and together, they weave their insights into a powerful prediction tapestry. This teamwork often results in a more accurate model than a single wizard could achieve.

2. **Resistance to Overfitting:** Random Forest is like a cool-headed mentor guiding its apprentices (decision trees). Instead of letting each apprentice memorize every training detail, it encourages a more well-rounded understanding. This approach helps prevent getting too caught up with the training data, making the model less prone to overfitting.

3. **Large Datasets Handling:** Dealing with a mountain of data? Random Forest tackles it like a seasoned explorer with a team of helpers (decision trees). Each helper takes on a part of the dataset, ensuring that the expedition is thorough and surprisingly quick.

4. **Variable Importance Assessment:** Think of Random Forest as a detective at a crime scene, figuring out which clues (features) matter the most. It assesses the importance of each clue in solving the case, helping you focus on the key elements that drive predictions.

5. **Built-in Cross-Validation:** Random Forest is like having a personal coach that keeps you in check. As it trains each decision tree, it also sets aside a secret group of cases (out-of-bag) for testing. This built-in validation ensures your model aces the training and performs well on new challenges.

6. **Handling Missing Values:** Life is uncertain, just like datasets with missing values. Random Forest is the friend who adapts to the situation, making predictions using available information. It doesn't get flustered by missing pieces but focuses on what it can confidently tell us.

7. **Parallelization for Speed:** Random Forest is your time-saving buddy. Picture each decision tree as a worker tackling a puzzle piece simultaneously. This parallel approach taps into the power of modern tech, making the whole process faster and more efficient for handling large-scale projects.

4. Proposed Ecosystem Control Architecture

A generic block diagram of control implementation using AI is shown in Figure 4. This generic figure can be applied to central monitoring and control of critical facilities and sub-systems, such as power systems, environmental control, distribution, etc.

- **Plant** is a general term that can be the temperature profile of a facility's power system or distribution system that powers different loads.
- **Actuators** represent control parameters of the plant, such as the HVAC system, power converters, voltage, and current setpoints or breakers in distribution.
- **Sensors** can be temperature sensors, voltage sensors, or current sensors.
- **Controller** is a piece of hardware that can be an ecosystem controller, power system controller, or BDFB controller.
- Higher level control resides in facilities in servers or a private cloud.
- External signals are the driving metrics to optimize the plant intelligently.

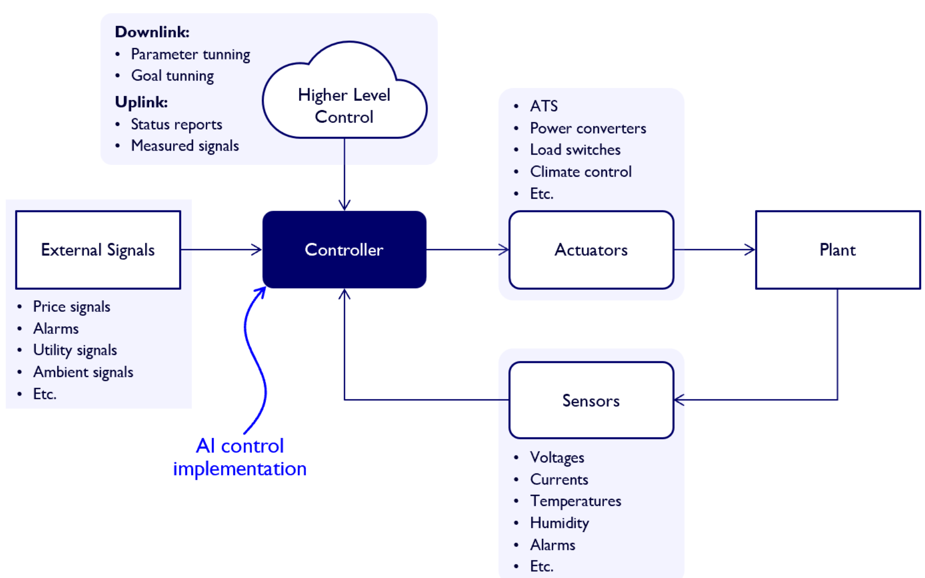

Figure 4: A generic diagram of the control problem view of AI control of a nanogrid The AI control can be implemented in the central controller. However, a similar structure is repeated inside the different elements, such as the power converter, allowing the system to operate autonomously if a higher-level controller fails.

Similar to hardware's single point of failure in the system, such as an ATS, there is a risk of a similar failure mode in the AI control model. Hence, this paper proposes a layered intelligence approach. This also allows for effective management of communications burden and processing power.

The proposed realization of the generic block diagram for nano-grid control for critical facilities is shown in Figure 5. This diagram represents higher-level artificial intelligence implementation. The ecosystem controller is connected to all the systems in critical facilities through a communications interface shown by blue dotted lines.

The ecosystem controller is focused on optimizing critical facilities performance based on example metrics such as, but not limited to,

- Utility pricing dynamics
- Utility planned maintenance
- Ambient signals, such as weather conditions

To perform these tasks, the ecosystem controller sends aggregated information from various system components to the "server/private cloud," where the machine learning models are built and updated. The output of machine learning results in parameter tuning and goal tuning outputs provided to the ecosystem controller.

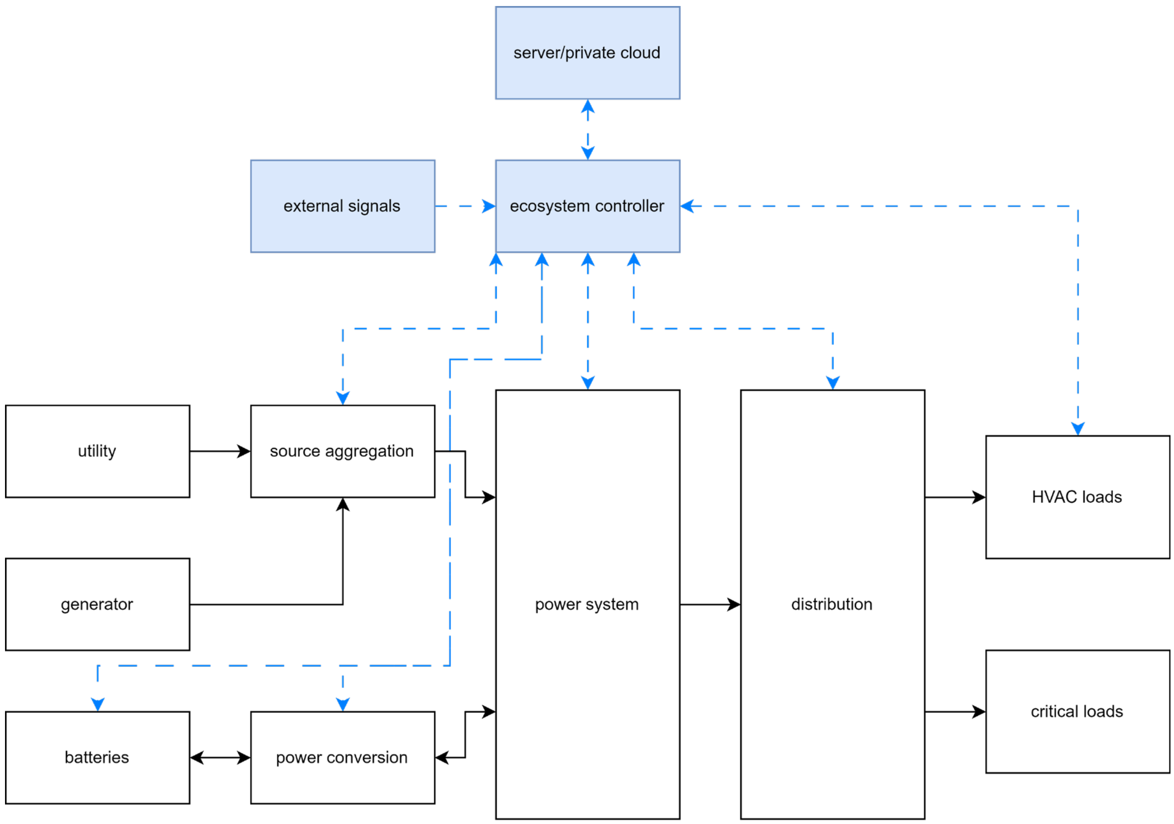

Figure 5: Block diagram of the nanogrid control and power architecture. Each component transmits signals and alarms to the ecosystem controller. The controller, in turn, transfers action commands such as set-points to each component, commanding them to move to a different state.

A layered/distributed intelligence approach is achieved through fractal representation of monitoring and control of lower-level power plants. For example, the ecosystem controller is connected to the source aggregation unit to monitor and control sources between the utility and the generator. Source aggregation also has the equivalent architecture of generic AI implementations, shown in Figure 6. Source aggregation receives higher-level control inputs from ecosystem controllers such as digital twin model updates, Source aggregation-specific setpoints, and thresholds. The source aggregation controller performs data aggregation from various sensors, sources, and aggregation components and performs onboard anomaly detection. The uplink from this controller to the ecosystem controller is knowledge of source aggregation sub-system and anomalies that can be used to update the digital twin models by a higher-level system.

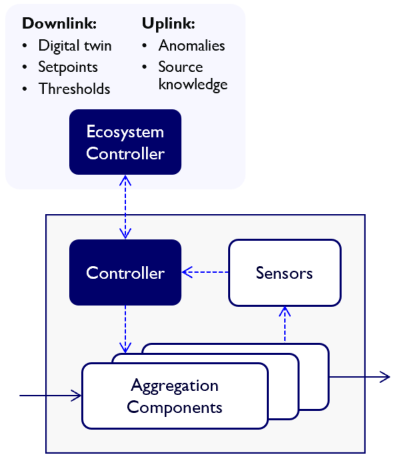

Figure 6: Diagram of the system's source aggregation components implementation. The control architecture is repeated at this lower scale, where the local controller can implement edge processing AI functions.

A similar fractal representation of the power system is shown in Figure 7. In this scenario, the power system controller performs anomaly detection and data aggregation to generate knowledge of the power system.

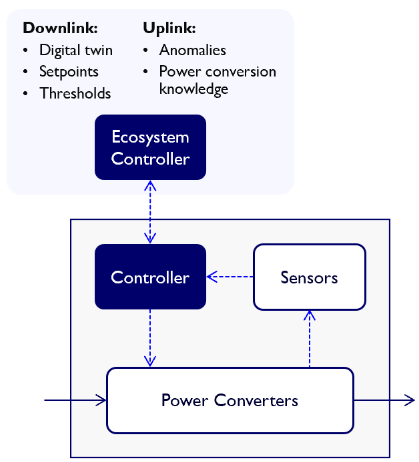

Figure 7: Diagram of the implementation of the power system component in the system. The control architecture is repeated at this lower scale, where the local controller can implement edge processing AI functions.

This layered intelligence approach preserves incumbent communications and control architectures and allows for seamless upgrades to the AI implementation. The power system and distribution sub-systems already have their respective controllers.

5. Distributed Intelligence Architecture

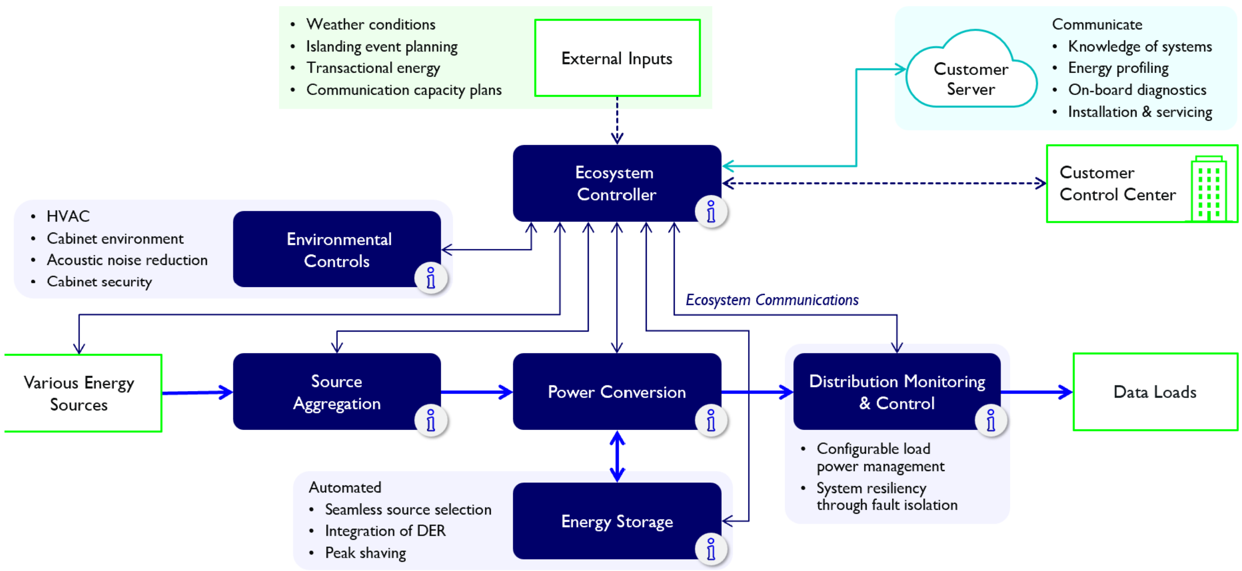

Figure 8: Distributed intelligence architecture with communications and processing

The thought process mentioned in the previous section results in the AI implementation architecture for critical facilities as generalized in the Figure 8The figure emphasizes communications structured to enable AI implementation. Black lines indicate communications, whereas power flow is shown with red lines. Messages communicated between every element of the ecosystem are no longer simple data such as voltage or current but information or knowledge of every subsystem. Distributed data processing can enable high-performance intelligence.

The proposed distributed intelligence approach depends on two key elements – communications and processing power.

5.1. Controller Communications

Traditional controller communications in critical facilities are based on physical layers such as CAN or RS485. The purpose of communications has been data transfer between two components, typically voltage, current, temperature, and setpoints for controls. In the layered intelligence approach, knowledge transfer and the transfer of models are important. New upcoming technologies such as Single Pair Ethernet (SPE) or Two Wire Ethernet can be used in such applications. This communications media improves speed by almost two to three orders of magnitude over traditional methods. For example, SPE 10BASE-T1 can reach 10Mbit/s over 1,000 m, while CAN is limited to 0.125 Mbit/s at 500 m. For shorter distances, SPE 1000BASE-T1 can reach 1,000 Mbit/s over 40m, while CAN is limited to 1 Mbit/s at the same distance.

Wireless communications can also be implemented, but communication security is essential, and it can be achieved through compliance with international standards such as IEC62443.

5.2. CPU Processing Power for AI Use

In typical feedback control systems, the controller aims to implement pre-programmed tasks. To perform data aggregation, high-speed communications, and anomaly detection, the controller CPU requires processing power improvement by order of magnitude. This results in the following improvements:

Table 2: Processing Power improvements

Parameter	Improvement
Software Upgrades	3x
Mib Building time	3x
Diagnostic File Exports	10x
CPU Usage	1/3x

The processing mentioned above power improvements can be accompanied by technology trends in silicon manufacturing, where new micro-processors with onboard AI suite capabilities are on the horizon. These capabilities allow for model imports, onboard diagnostics, and anomaly detection capabilities. We envision using such technology trends to drive more distributed analytics architectures.

6. Example AI Application: Energy Management

Of particular interest to the nanogrid operation and a possible application of AI is the selection, in near real-time, of the optimal mix of energy sources. This is known as energy management.

Energy management can be divided into the following functions including, but not limited to,

1. Source Selection based on planned activities or utility stress
2. Peak Shaving
3. Utility cost reduction for peak demand charges

The Figure 9 shows the realization of the energy management application for the critical facility. The energy sources listed are utility, generator, portable generators, Distributed Energy Resources (DER) such as solar photovoltaic (PV), and Battery Energy Storage systems.

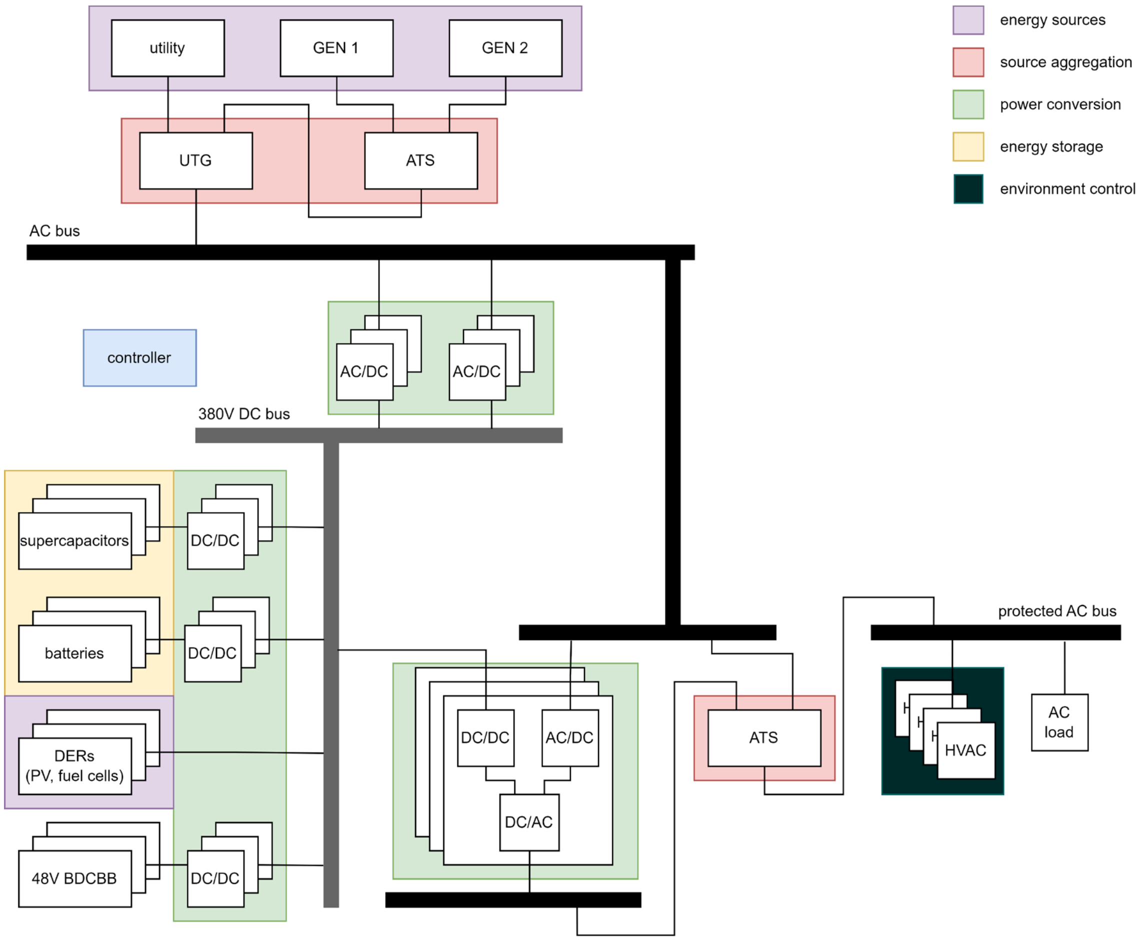

Figure 9: Distributed AI Application for Energy Source Management

Energy management can be viewed as a binary selection of sources between Utility and generator. It can also be a complex mix of various sources by sharing the energy to maintain the Essential DC bus in the proposed nanogrid.

6.1. Individual Source Selection

In planned utility outages, energy source selection can be programmed by knowing outage times beforehand. An Ecosystem controller can provide actionable outputs to request preemptive generator maintenance to ensure resiliency.

Similarly, in case of impending poor weather conditions, an ecosystem controller can transition the system to a resilient power source in anticipation of a potential disruption due to utility interruption.

6.2. Multiple Energy Source Sharing

Power conversion or other source aggregation components allow for sharing various energy sources to maintain the essential DC bus. At each instant, the ecosystem controller must decide how much power to take from each source. This decision may be influenced by external signals (like the price of utility energy at this moment), environmental conditions (such as the amount of photovoltaic energy available), and its internal state (such as the state of charge or the total load).

Table 3 shows the typical alarm thresholds for various sources and components in a critical facility. Reliability requirements drive these thresholds. Hence, the status of energy sources and power plants is critical in defining the usage of sources for energy management. For example, when a generator is used for backup or energy management, the fuel level will drive the decision to use the generator optimally.

Table 3: Alarm threshold settings in a typical critical facility

Alarm Threshold Settings				
Threshold Settings	LOW MN	LOW CR	HIGH MN	HIGH CR
Facility Power:				
Utility Voltage (Normal Voltage)	90%	80%		110%
Voltage (Output side of ATS) (Nominal Voltage)	90%	80%		110%
Frequency (Output side of ATS)		95%		105%
Generator:				
Fuel Tank Level	35%	20%		
Battery Start Voltage		90%		
UPS:				
Input Voltage (All Phases)	90%	80%		110%
Output Phases (All Phases)		90%		110%
Output Power (All Phases) 80% of UPS Capacity			80%	
DC Plant:				
System Current (Not in Discharge)			80%	90%
System Float Voltage (Nominal Voltage - 54Vdc)	46Vdc	42Vdc		55.5Vdc
HVAC:				
Room Temperature (Nominal Temperature 72 degrees F)		60 F		85 F
Security/BMS				
Door Open			10 Min Delay	

Moreover, the decision must meet several constraints while maximizing several competing goals. At a given moment, for example, utility energy may be expensive, and photovoltaic may be available to cover a significant portion of the load; this would encourage the ecosystem controller through source aggregation controller to minimize the utility power while maximizing Renewable Energy sources/photovoltaic power (reduce cost and carbon footprint of the system). However, the battery energy storage may be low, compromising the system's reliability in case of a blackout. This situation would force the controller to weigh the low energy storage risk exposure against the financial and environmental benefits of only using photovoltaics.

Some decisions are simple: if there is a utility outage at night, the nanogrid cannot draw power from the utility or photovoltaic. Therefore, the nanogrid may draw power only from the batteries, as an alternative may not exist. Some decisions are complex: Should the nanogrid reduce the HVAC during a heatwave with a relatively low load, letting the system run hotter and reducing its lifetime, and can it provide extra hours of backup time during an outage? How much can the HVAC be reduced?

Some decisions are binary: the ATS can be connected to the utility or the generator, not both. Some decisions are continuous: the rate of charge or discharge of a battery can be controlled continuously. Some decisions are discrete: how many load channels should be enabled?

The resulting overlap of the competing objectives and the type and number of decision variables will likely result in a dynamic hybrid non-convex optimization problem. This problem may be where an AI algorithm (such as the Random Forest) implemented in the nanogrid's ecosystem controller can excel. Furthermore, the AI can benefit from learnings obtained in the past to update itself and from access to a remote repository of models and learnings from other such nanogrids.

6.1. Use Case of Energy Source Sharing

Let’s take an example of a critical facility with a 600kW power plant. Traditionally, all the power is delivered by utility. In case of a renewable source of 100kW being available, a simple pre-programmed algorithm can be used to use renewable sources during peak energy charges to reduce energy costs. Similarly, if 100kW of Battery Energy Storage System (BESS) is available, then it can be used at peak utility charges and can be charged back during low energy charges, as shown in Figure 10 and Figure 11. Each scenario can be implemented with a standard feedback control loop or even open loop control methodologies.

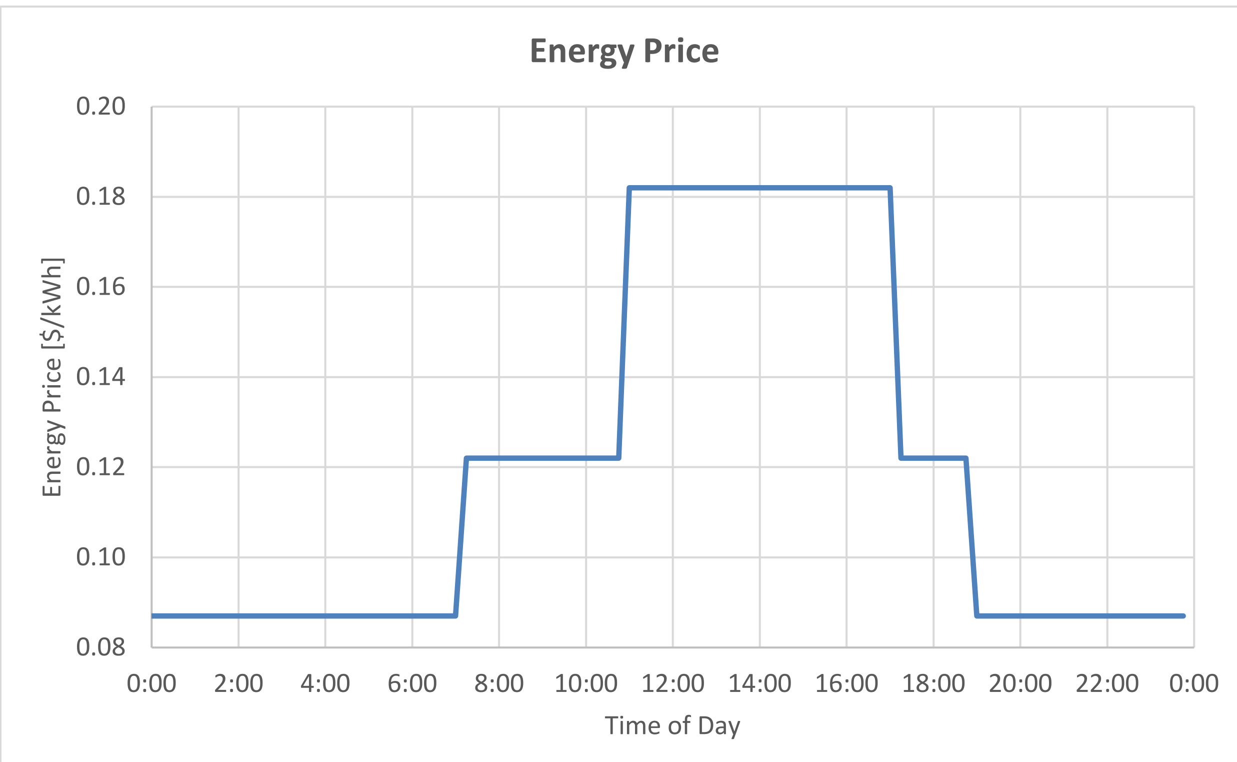

Figure 10: Sample time-of-use energy price showing peak and off-peak utility charges from Toronto Hydro [5].

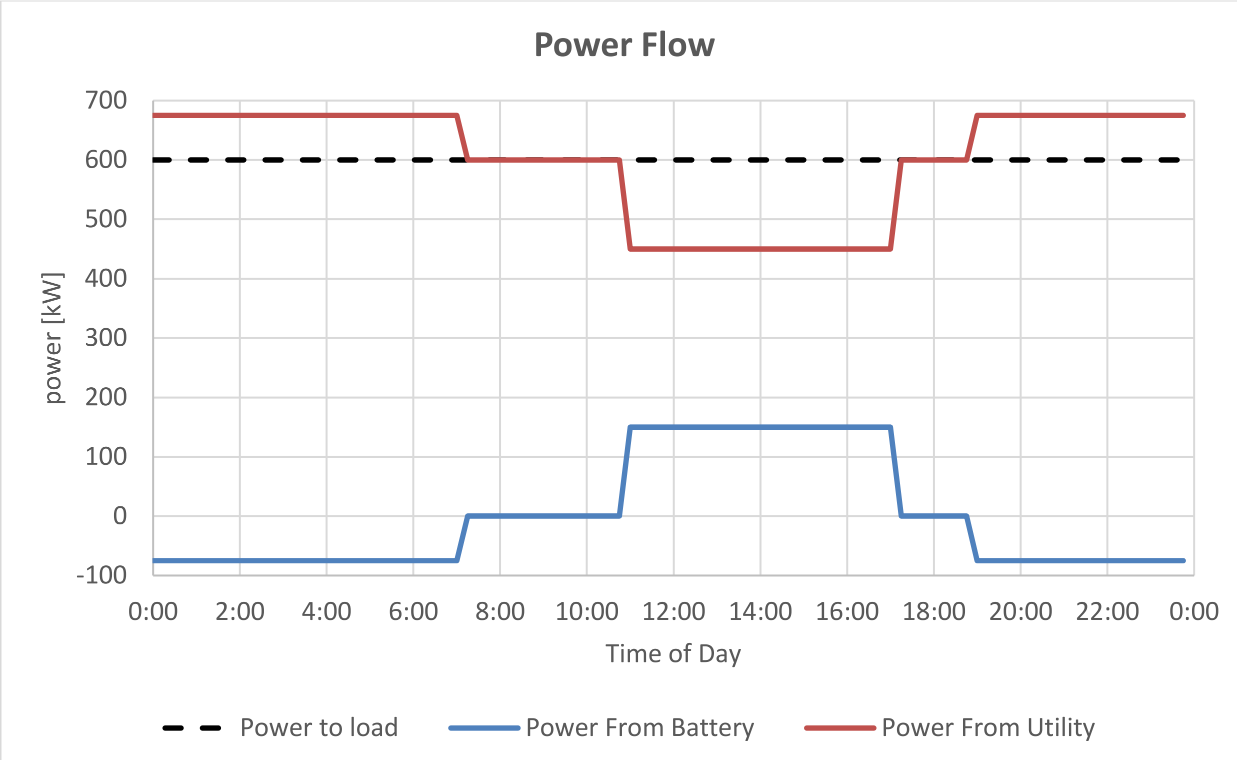

Figure 11: Dynamic power flow from utility and batteries to feed a sample 600kW load; during the peak price time, the system draws power from the BESS and returns it during the off-peak price time, resulting in cost savings for the system.

However, when we have multiple sources available, the choice of energy source is a complex problem. To add realistic complexity, every source may have fluctuations in available energy, such as poor battery strings, resulting in a lower state of charge. In such cases, reliability is very important. This information will be available over sub-system level controllers such as source aggregation controllers. The distributed intelligence at source aggregation controller, shown in Figure 6, will feed knowledge of energy sources based on models and anomalies to the ecosystem controller. The ecosystem controller then uses this information to feed the AI algorithm, such as a random forest. The decision tree builds optimal control functions for each source aggregation. Multiple metrics, such as energy cost reduction, energy efficiency, and carbon credits, can drive the decision.

The sub-system level controller then uses the control functions and makes lower-level decisions based on the status of the energy source instead of making a simple decision of turning ON or OFF the energy source. The advantage of such distributed intelligence is that it improves resiliency. If the control function is not implemented, it will continue to operate the system at its optimal point and give feedback on the information to the ecosystem controller. This allows for reinforcement learning in the ecosystem.

AI implementation will reduce human decision-making requirements and optimize energy usage and cost while preserving the system's reliability. This system can reduce energy and optimize energy cost-effectively by transitioning the electrical system to the best, least costly source.

7. Conclusion

This paper provides an overview of the role of Artificial Intelligence in the infrastructure of critical facilities based on a nanogrid. For instance, it explores how the random forest machine learning technique can determine the best combination of energy sources in real-time.

In addition to enhancing resiliency, nanogrid architecture allows AI to optimize critical facilities for reliability, energy efficiency, and operational cost reduction. Advancements in communication and processing power support the implementation of distributed AI, reducing the reliance on single ecosystem controllers and enhancing resiliency. The application of AI to nanogrid architecture facilitates energy management, eliminating the need for human intervention and enabling the optimal utilization of various energy sources, which was not feasible in previous power system architectures.

Abbreviations

AI	Artificial Intelligence
Mib	Management Information Base for SNMP devices.
ML	Machine Learning
SCTE	Society of Cable Telecommunications Engineers

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