EESA
PROJECT
REPORT

ML & AI in Power Systems

Electrical Engineering Department

Written By : Ali Jafari

January 2022

Contents

Preface

As the machine-learning industry evolves, the focus has expanded from merely solving the problem to solving the problem better.
"Better" often has meant accuracy or speed, but as data center energy budgets explode and machine learning moves to the edge, energy consumption has taken its place alongside accuracy and speed as a critical issue. There are a number of approaches to neural networks that allow for reductions in energy consumption.

" **Everybody's looking for alternate ways of implementing neural networks that are going to be much lower power,**" said Elias Fallon, software engineering group director, custom IC & PCB Group at Cadence.

"**Google itself is worried about the power during the creation and training of the neural net,**" said Venki Venkatesh, director of R&D, AI & ML solutions, digital design group at Synopsys.

Finally, by analyzing the existing ideas and approaches, we figure out how AI & ML are affecting the Power Management in cities, industries , and power plants.

2 What is AI ?

Artificial intelligence generally refers to processes and algorithms that are able to simulate human intelligence, including mimicking cognitive functions such as perception, learning and problem solving. Machine learning and Deep learning (DL) are subsets of AI.

Specific practical applications of AI include modern web search engines, personal assistant programs that understand spoken language, self-driving vehicles and recommendation engines, such as those used by Spotify and Netflix.

3 What is ML ?

In a nutshell, machine learning is a subset of AI that falls within the ”limited memory” category in which the AI (machine) is able to learn and develop over time.

There are a variety of different machine learning algorithms, with the three primary types being supervised learning, unsupervised learning and reinforcement learning.

4 How AI & ML affect Energy

Energy providers around the world are also in the middle of an industry transformation, with new ways of generating, storing, delivering and using energy changing the competitive landscape. Additionally, global climate concerns, market drivers and technological advancements have also changed the landscape considerably.
The energy sector is already using AI/ML to develop **intelligent power plants**, optimize consumption and costs, develop predictive maintenance models, optimize field operations and safety and improve energy trading.

5 Technology-based energy business strategies

Technology is a root cause of—and a solution to—utility market disruption. Power companies cannot rely on legacy systems to remain competitive. Instead, technology leaders must offer Industry 4.0 technologies, embedded in strategies for business growth and competitive advantage.

5.1 Put data into the customer experience

Consumers want real-time access to electric consumption data to help them analyze usage patterns and reduce costs.

Customer-facing interfaces like online portals and mobile apps offer this data access to residential users. Using data to enhance the customer experience can help increase customer loyalty and grow revenue.

5.2 Use analytic tools to optimize consumption and costs

The addition of analytic tools to user interfaces helps residential and business customers and energy providers predict, manage, and optimize energy consumption. Through data capture from sources like process monitoring, automation, and production planning systems, energy companies can make decisions that help optimize energy generation, procurement, and usage.

5.3 Establish intelligent power plants

IT and operations technology (OT) still rely on legacy systems and applications in power plants. Today's technology solutions can take advantage of sophisticated data capture and management that form the foundation of intelligent systems. Edge computing, automation, real-time monitoring, and other capabilities can transform plant operations.

5.4 Upgrade transmission line monitoring, maintenance

Intelligent systems can substantially increase efficiency and reliability of electric transmission. Automation and real-time monitoring can streamline workflows and increase maintenance effectiveness.

5.5 Maintain regulatory compliance

As the electric industry rapidly evolves, so does its regulatory environment. The data capture that improves operations and management also helps to ensure compliance and streamline regulatory documentation processes.

6 Examples of Artificial Intelligence in Power Plant

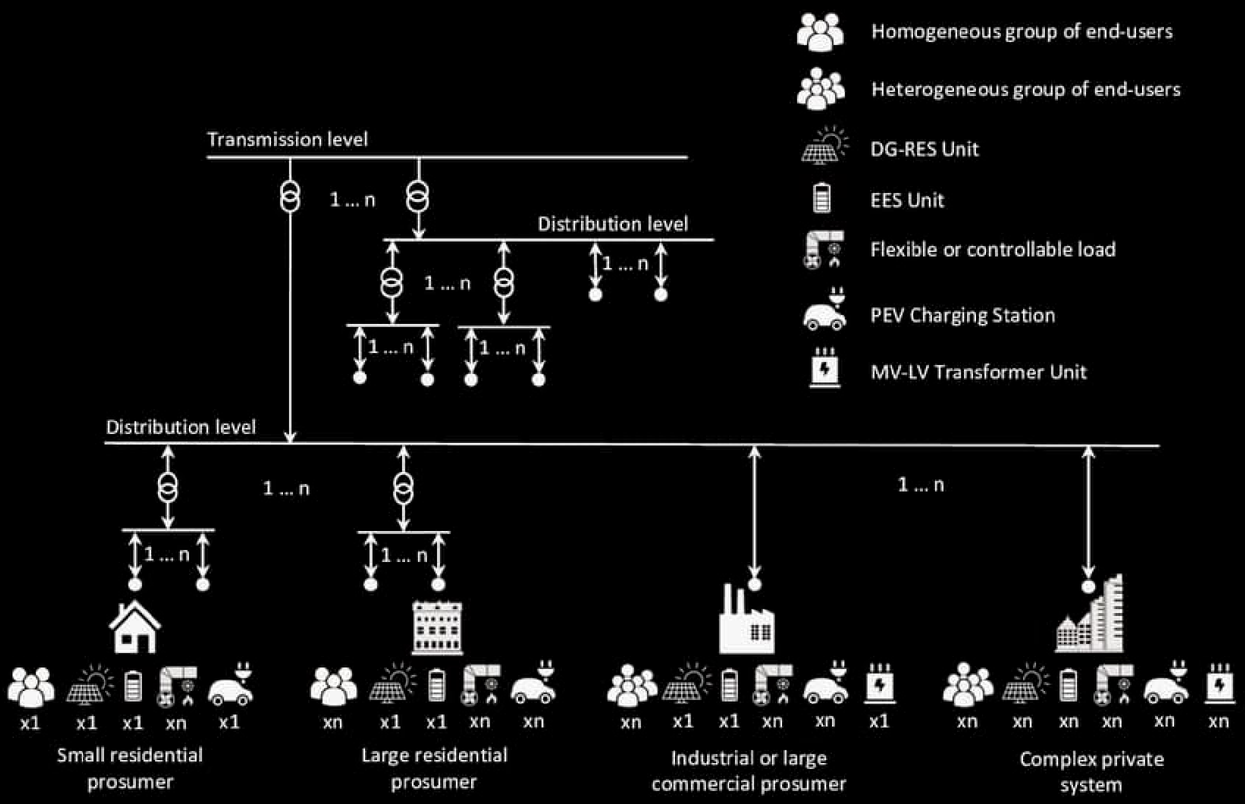
6.1 (AI + Energy Storage) = Athena

Stem, a San Francisco-based company founded in 2009, brings together the power of AI and energy storage to "optimize the timing of energy use". Through the combination of machine learning, predictive analytics and energy storage, Athena, as the system is called, forms virtual power plants to maximize the value of energy storage.

How does it do this?

Through analysis of data at a rate of 400 megabytes every minute, the system continuously assesses the time value of energy and makes the most optimal decisions about when energy should be purchased. The process of aggregation across multiple points representing energy storage capacity is what is described as the "virtual power plant". The proliferation of these distributed resources are increasingly being driven by the growth of what are called distributed energy resources (DER) on the electric grid – primarily through rooftop solar which has grown significantly over the past decade.

The image below provides a rendering of this concept :



In this example, EES refers to Electrical Energy Storage; DG refers to Distributed Generation; and MV and LV refer to medium voltage and low voltage respectively.

The process of this aggregation into a virtual power plant is conducted continuously, leveraging AI to develop predictive analytics across a variety of variables – such as weather, energy consumption levels, tariff (electricity rate) options, among others and automate the process of real-time calculations. The result provides aggregated load reductions that can provide relief during periods of unprecedented heat waves (though thanks to climate change becoming less unprecedented). This is something that the Stem system deployed more than 600 times in the California wholesale market in 2017.

6.2 AI Facilitates Renewable Energy Management

As the impact of climate change and continued use of fossil fuels drives renewable energy growth – now accounting for a fifth of global electricity production, there is one aspect of this growth that many may not realize. Increasing the amount of renewable energy presents challenges to system operators to integrate these sources into the existing electric grid.

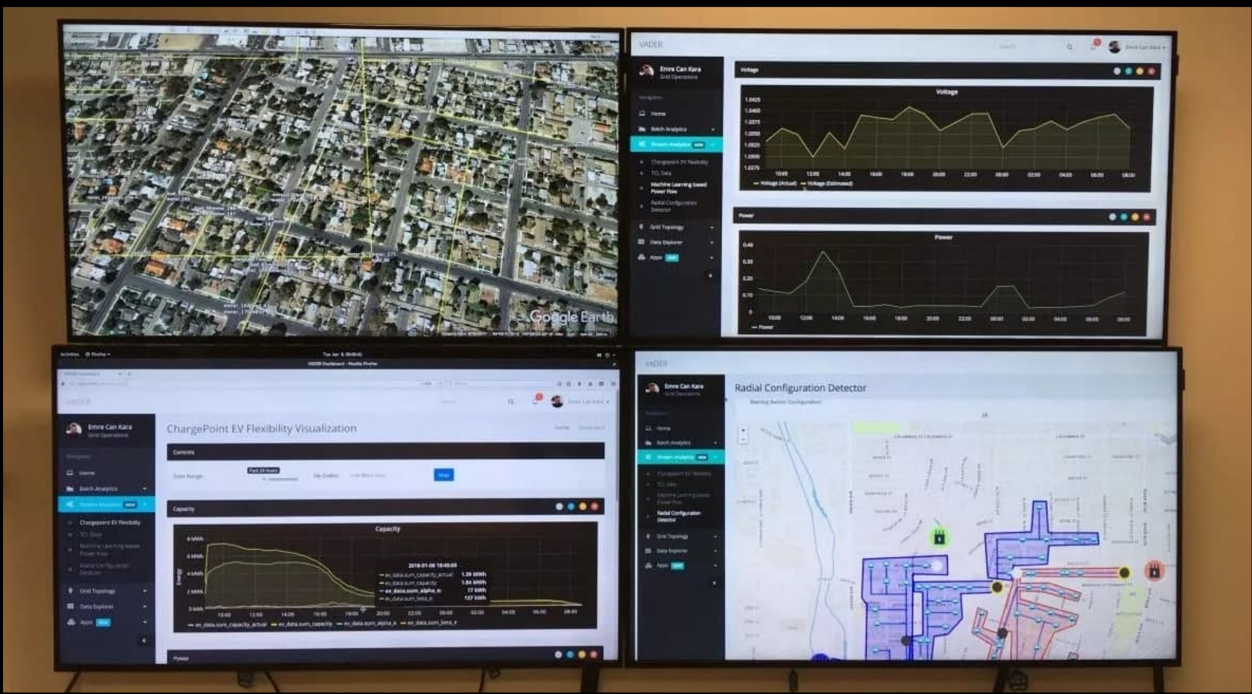
Since solar or wind could be impacted simply by random clouds or difficult to predict wind patterns, this challenge is compounded on a minute-by-minute basis to ensure that the electric grid continues to maintain consistent, reliable power. This is another area where AI shines (no pun intended). We profile two such innovations below – the first is associated with managing solar resources and the second involves aggregating multiple streams of data and combining weather forecasting and machine learning to optimize renewable energy operations.

6.3 VADER – Visibility into Distributed Energy Networks

VADER – Visibility into Distributed Energy Networks Clearly the brainchild behind this effort was a Star Wars fan; no, Vader here does not refer to the dark lord, but rather to a platform combining data from photo-voltaic (PV) solar systems and smart meters which crunch data on a continuous basis to model electricity consumption and behavior of distributed energy resources such as rooftop or ground-mount solar. VADER stands for Visualization and Analytics of Distribution Systems with Deep Penetration of Distributed Energy Resources (or, again, DER).

The engine at the core of all this innovation is machine learning and AI-based algorithms; it can "model potential changes in connectivity and the behavior of DERs on the grid, enabling the real-time optimization and automation of distribution planning and operation decision for utilities".

Below is a glimpse at some of the platform's application screens.



6.4 What is Salt River Project (SRP)

In 2019, Tempe, Arizona-based public power utility Salt River Project (SRP) signed a deal to use AI to improve its information technology (IT) operations. The Phoenix-based public power utility adopted ScienceLogic's SL1 platform to monitor its IT operations and applications.

In a Q&A with Public Power Current, Joe Kosmal, manager of data center operations at SRP, said that SRP completed phase one of the ScienceLogic implementation in July 2020, which was a value-added replacement of SRP's legacy IT operations platform.

"We are currently well into our phase two project which includes the advanced capabilities to assess the health, availability, and risk to applications and systems that serve critical business processes in the enterprise," he said.

Kosmal was asked to discuss how ScienceLogic's platform has improved SRP's IT operations since its implementation.

"Since implementation, ScienceLogic has helped us regularly identify issues before they caused impact to the reliability and resiliency of our IT systems," he said. "This has helped mature our IT operations from reactive monitoring and escalations to proactive monitoring that fosters a stronger partnership with application and system support teams in the organization."

When asked whether SRP is considering deploying AI in any other parts of its operations beyond IT, he said SRP is exploring use cases for AI in different areas of the utility and evaluating how those capabilities can improve operations and better serve SRP customers.

6.5 What is New York Power Authority (NYPA)

Meanwhile, the New York Power Authority (NYPA) has been awarded two $125,000 grants from the American Public Power Association's Demonstration of Energy & Efficiency Developments (DEED) program to fund demonstration projects that will analyze the impact of ice on a hydropower plant and test an advanced technology that evaluates the health of high voltage assets in a substation.

The DEED program funds research, pilot projects and educational programs to improve the operations and services of public power utilities.

NYPA will undertake the following projects :

Analyze the Impact of Ice on Hydro Power Resources with Machine Learning: NYPA has had significant power generation losses due to ice blockages near intake valves in the Niagara River and has worked to address the issue with industry groups and other utilities. During the winter, water can become supercooled all the way to the bottom of the river, leading to the formation of frazil ice crystals, anchor ice, or both. Anchor and frazil ice affects water availability estimation by Niagara River Control Center and frazil ice can affect hydropower plan operation since it's "sticky" and can result in ice formation on the plant's water turbines. These studies will include using 3-D sonar to quantify the impact of frazil ice on the efficiency of the hydropower units and forecasting the formation of anchor and frazil ice with a look ahead of a few days to a few weeks.

Smart Insulation Condition Monitoring System (CMS) for Substation Assets: A state-of-the-art Condition Monitoring System will be developed to constantly monitor the insulation condition of various high voltage assets (transformers, GIS, switchgears and cables) in a substation. The CMS consists of smart sensing, advanced noise mitigation and artificial intelligence for data interpretation. The system will use an advanced diagnostic technology that recognizes and evaluates defects and provides guidance for maintenance planning. The system will improve the power grid reliability, reduce customer outage costs, and help asset management optimize maintenance and maximize asset life.

NYPA deploys AI-based application :

In 2018, NYPA selected C3 IoT to provide a software platform to help NYPA and the state implement and meet its energy efficiency targets.
Under a multi-year, software-as-a-service agreement, NYPA agreed to deploy C3 Energy Management, an AI-based application, as part of New York Energy Manager, NYPA's advanced, secure energy management center, headquartered in Albany, N.Y. It provides public and private facility operators across New York State with timely data on energy use.

The C3 Energy Management application enables the New York Energy Manager program to aggregate enormous volumes of data, including real-time data from smart meters, building management systems, end-use equipment controls, sensors, weather data, occupancy and daylight data, solar data, and utility bills.

C3 IoT said the application would allow the New York Energy Manager program to employ machine learning at scale, generate insights about individual customers' energy usage, and deliver personalized recommendations to help customers reduce their energy use.
The company said the software would also allow NYPA to offer its customers services such as building energy load forecasting, fault detection and diagnostics, continuous optimization of energy use, dynamic demand response, solar and energy storage monitoring, and aggregation and dispatch of buildings as distributed energy resources.

New York Energy Manager "is utilizing C3's Energy Management application to help our customers reduce their energy costs, improve their building operations, and track and report their progress towards energy efficiency and sustainability targets," said Paul DeMichele, Manager, Media Relations, at NYPA. The application gives New York Energy Manager advisors "visibility into customers' energy use and expenditure, helps them identify and prioritize actions to reduce operational and energy-related costs, and reduce their carbon footprint."

7 How AI Upgrades Customer Experience

Artificial Intelligence is rapidly transforming many elements of our lives, including the utilities market.

7.1 Curbing high energy bills with predictive analytics

Predictive analytics are helping utilities provide better energy management services by utilizing data, statistical algorithms and machine learning techniques to identify the likelihood of future outcomes based on historical data. For utilities, that means using data-driven insights to automatically deliver timely and relevant communications that wow consumers and optimize business operations.

According to Oracle, smart meters in the US generate one billion customer data points each day – that's three thousand times more information than the old meters would collect.

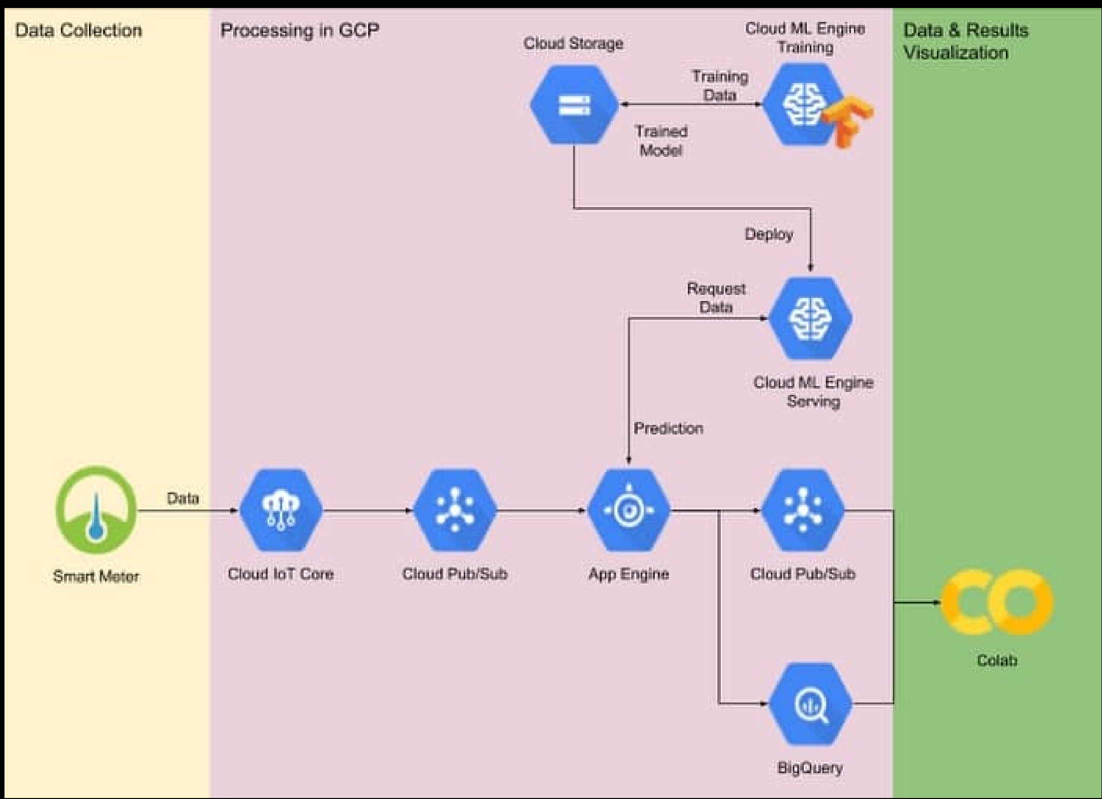
Add to that customer information from demographics and call history, and utilities have all the data they need to predict customers' wants and needs. For example, AI-based predictive analytics can help energy companies forecast high bills before the bills are generated, and deliver personalized alerts to customers. AI also allows utility companies to segment customers and automatically target specific segments for promotions or energy-savings tips, thereby reducing operational costs, and further cutting customers' energy bills.

7.2 Google Cload IOT Core in Home Appliances

The growing popularity of IoT devices and the evolution of machine learning technologies have brought new opportunities for businesses. In this post, you'll learn how home appliances' (for example, an electric kettle and a washing machine) operating status (on/off) can be inferred from gross power readings collected by a smart meter, together with state-of-the-art machine learning techniques.

An end-to-end demo system, developed entirely on Google Cloud Platform , includes:

- Data collection and ingest through Cloud IoT Core and Cloud Pub/Sub
- A machine learning model, trained using Cloud ML Engine
- That same machine learning model, served using Cloud ML Engine together with App Engine as a front end
- Data visualization and exploration using BigQuery and Colab

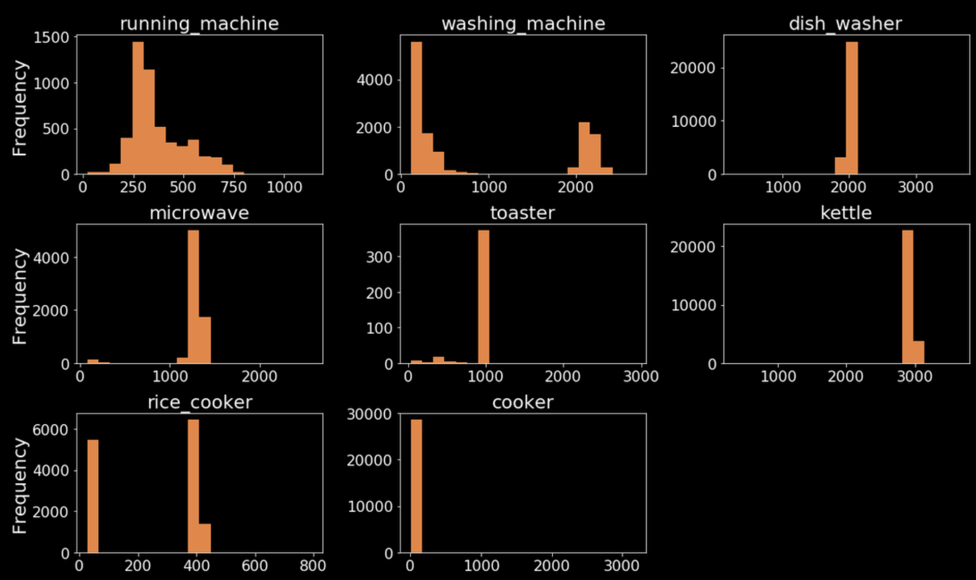


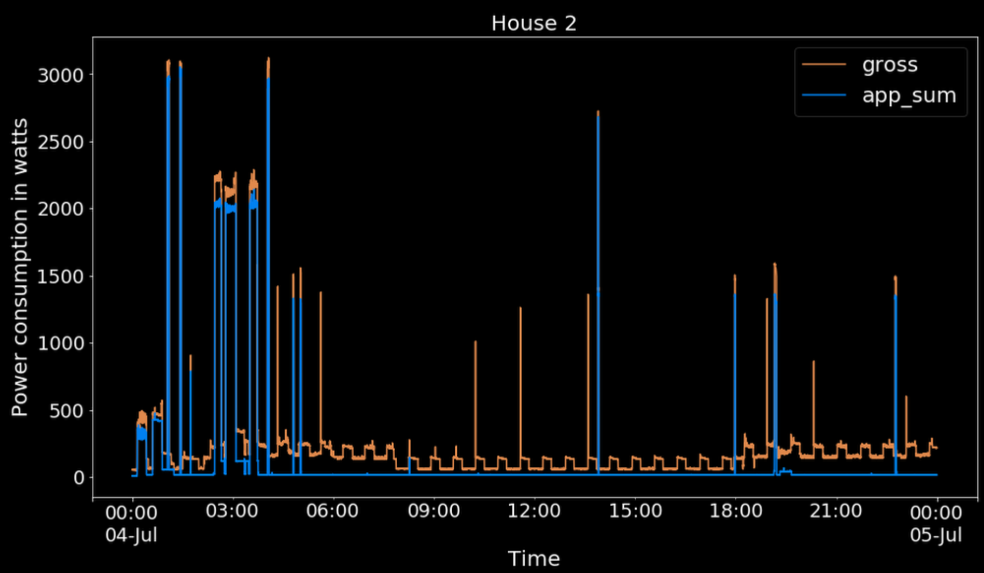
We trained our model to predict each appliance's on/off status from gross power readings, using the UK Domestic Appliance-Level Electricity (UK-DALE, publicly available here) dataset in order for this end-to-end demo system to be reproducible. UK-DALE records both whole-house power consumption and usage from each individual appliance every 6 seconds from 5 households. We demonstrate our solution using the data from house #2, for which the dataset includes a total of 18 appliances' power consumption. Given the granularity of the dataset (a sample rate of $\frac{1}{6}$ Hz), it is difficult to estimate appliances with relatively tiny power usage. As a result, appliances such as laptops and computer monitors are removed from this demo. Based on a data exploration study shown below, we selected eight appliances out of the original 18 items as our target appliances: a treadmill, washing machine, dishwasher, microwave, toaster, electric kettle, rice cooker and "cooker," a.k.a., electric stovetop.

The figure below shows the power consumption histograms of selected appliances. Since all the appliances are off most of the time, most of the readings are near zero. Figure below shows the comparisons between aggregate power consumption of selected appliances (app_sum) and the whole-house power consumption (gross).

It is worth noting that the input to our demo system is the gross consumption (the blue curve) because this is the most readily available power usage data, and is even measurable outside the home.

In Figure below you can see Target appliances and demand histograms.





The data for House #2 spans from late February to early October 2013. We used data from June to the end of September in our demo system due to missing data at both ends of the period. The descriptive summary of selected appliances is illustrated in Table 1. As expected, the data is extremely imbalanced in terms of both "on" vs. "off" for each appliance and power consumption scale of each appliance, which introduces the main difficulty of our prediction task.

	cooker	running machine	toaster	washing machine	rice cooker	kettle	microwave	dish washer
count	878400	878400	878400	878400	878400	878400	878400	878400
mean	0.18	2.88	0.588	11.27	2.92	22.138969	6.75	39.53
std	4.95	15.09	16.89	120.65	27.01	248.66	90.99	271.85
min	0	0	0	0	0	0	0	0
25%	0	1	0	3	1	1	0	1
50%	0	1	0	3	1	1	0	1
75%	0	1	1	4	1	1	0	1
99.9%	10	296	1	2193	406	2994	1331	2039
99.99%	10	372	971	2305	412	3051	1357.16	2072
max	3532	718	2364	2974	807	3996	2668	3955

7.3 Virtual Assistants for Smart Home Products

These smart home devices generate a massive number of support requests for installation, set up, troubleshooting and maintenance, often overwhelming customer support centers. Utilities can implement AI self-service capabilities that instruct customers how to install and operate smart devices by themselves.
For example, an AI-powered virtual technician can use computer vision to view the customer's environment and provide a step-by-step unboxing experience, including installation and activation instructions. This eliminates the need for the customer to contact a human agent for assistance.

8 Other Uses of AI in Utilities

Beyond the customer-facing experience, AI has also proven to be exceedingly useful to utilities in managing internal processes and back-office tasks. For example:

- **Load Forecasting** : Utilities use AI-based load forecasting algorithms to predict how much power must be generated to meet the short term, medium term or long term demand of their customers.

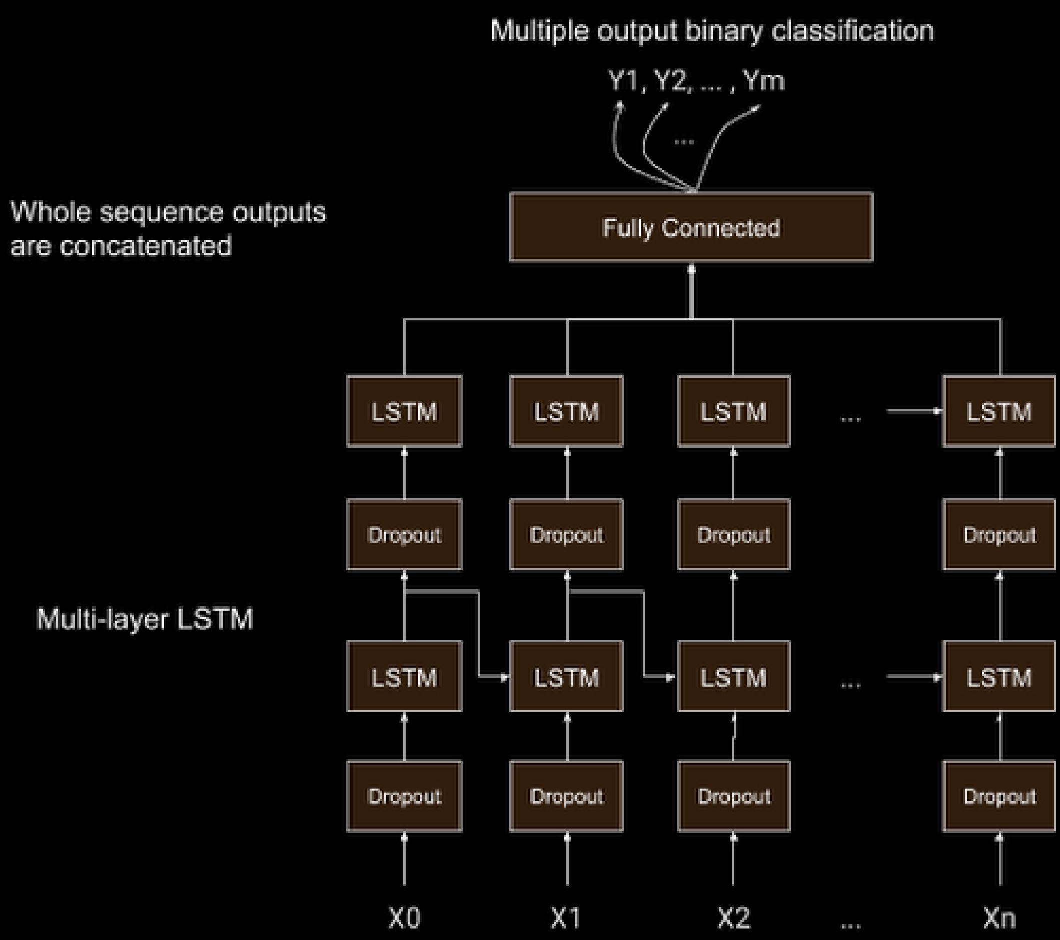
- **Yield Optimization** : For better ROI, utilities are using AI-driven data analysis and other optimization techniques to maximize their power generation efficiency with real-time monitoring and adjustments.
- **Energy Theft:** Fraud or outright theft is not uncommon in certain countries. AI can be used to detect usage patterns, customer data, payment history, and other variables that can flag suspicious activity.

9 A Brief Overview on ML Models and Networks

The Machine Learning Model

We adopt a long short-term memory (LSTM) based network as our classification model. Please see Understanding LSTM Networks for an introduction to recurrent neural networks and LSTMs. Figure in next page depicts our model design, in which an input sequence of length n is fed into a multilayered LSTM network, and prediction is made for all ”m“ appliances.

A dropout layer is added for the input of LSTM cell, and the output of the whole sequence is fed into a fully connected layer. We implemented this model as a TensorFlow estimator.



Conclusion

It goes without saying that updating old and inefficient systems can improve production processes and quality. But artificial intelligence (AI) technologies have evolved to be able to do so much more.

In buildings and factories, AI can monitor and collect information about energy consumption in the form of numbers, text, images and videos. Evaluating what is observed, AI can manage energy usage, reducing it during peak hours, for example. Problems such as bottlenecks can be identified and equipment failures detected – even before they happen.

On a larger scale, AI has the ability to compress and analyse data to predict future problems, and ultimately optimise energy consumption in the long term.

While this surpasses what has previously been possible for humans to do alone, it still requires the personal touch. Technicians need to be trained to tailor each AI solution to address specific problems in their own processes.

This technology may come at a cost, but savings as a result of efficiencies can be significant – up to 60% promised by some players – so it can pay for itself within a short period of time.