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Smart utility systems for rural electric cooperatives

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Final Report: Smart utility systems for rural electric cooperatives

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Rural communities are facing pressure to increase broadband connectivity for their residents to maintain economic growth, however, due to their low populations, broadband projects are typically not financially feasible with current investment models. The Post Road Foundation project team evaluated the financial feasibility of distributed wind and solar energy resources for Presque Isle Electric and Gas (PIEG), a utility cooperative in Northern Michigan. The team identified that solar installations for Commercial and Industrial customers in the 250kW range could be financially viable due to increased array sizes and rate structure incentives. In order to further test the feasibility of solar and battery arrays for larger utility customers, the team built a long short term recurrent neural network to aid in prediction of future load profile. This load profile was used to optimize solar array and battery size to minimize capital investment costs and reduce payback periods.

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Individual Contributions to the Report (Liwei Chen)

My individual contributions to this project include the following, serving as the team leader for the first

semester, financial and market analysis for utility investment payback, conducting literature review for

alternative distributed energy technologies such as biomass, developing optimization function for a

combined solar and battery install for commercial and industrial customers, and feasibility analysis for

residential and commercial solar installations, as well as distributed wind, using NREL's System Advisory

Model tool. My specific contributions to the report are also listed with my initials "LC" as the author in the

section header which are sections 1, 2.1, 2.2, 3.2, and 4.1 through 4.5.

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Executive Summary

Rural communities are facing pressure to increase broadband connectivity for their residents to maintain economic growth, however, due to their low populations, broadband projects are typically not financially feasible with current investment models. Distributed energy resource technologies offer a new opportunity to both bring broadband connections to rural communities and improve grid utilization and resilience. However, many rural cooperatives are either not familiar enough with the advantages of new distributed renewable energy technologies or do not have enough utility consumption data to optimize their installation with existing power generation.

The Post Road Foundation project team evaluated the financial feasibility of distributed wind and solar energy resources for Presque Isle Electric and Gas (PIEG), a utility cooperative in Northern Michigan. The team found that distributed wind and solar at the residential level are not currently financially viable with payoff periods exceeding 20 years due to low solar and wind resources. However, the team identified that solar installations for Commercial and Industrial customers in the 250kW range could be financially viable due to increased array sizes and rate structure incentives.

In order to further test the feasibility of solar and battery arrays for larger utility customers, the team built a long short term recurrent neural network to aid in prediction of future load profile. This load profile would be used to optimize solar array and battery size to minimize capital investment costs and reduce payback periods. The team used publically available utility data from the Northeastern United States for utility customers in the same industries as PIEG as training data. However, when the recurrent neural network was applied to the PIEG data to predict future electric load profiles, the machine learning model could only predict several weeks beyond the scope of the dataset before converging to an average load value. Analyzing the model's limitations, the team identified that while the model was well trained, the team did not provide enough parameters for the model to learn all the correlations between the training data set's patterns and the actual load data. With further parameter design and expansion, our neural network model may be able to provide year long prediction intervals to aid in load prediction for rural cooperatives with limited load data.

Index Terms - Distributed Energy Resources, Synthetic Load Profile, Recurrent Neural Network, optimization, Presque Isle Gas and Electric, Post Road Foundation

1. Introduction

[Author: LC, Reviewer: ZZ] The Post Road Foundation (PRF) team is focused on improving broadband connectivity for rural utility cooperatives in the United States. PRF helps communities develop intelligent, broadband-connected infrastructure to drive digital inclusion, efficient resource management and economic growth by focusing on Distributed Energy Resources (DER) and Distributed Generation (DG) technologies. DER and DG technologies include small scale electricity generating equipment such as rooftop solar, wind turbines, batteries or microturbines optimized with broadband connectivity. These technologies offer benefits to end-users to either provide backup power, or to reduce their peak electric consumption in order lower their electric rates. PRF is working with Presque Isle Electric & Gas (PIEG), a distributing utility cooperative in northeastern Michigan (MI) to harness the rising market for DER and DG.

Rural cooperatives have struggled to install and adopt DER technologies at a similar pace with investor owned utilities such as Pacific Gas and Electric. Unlike investor owned utilities, rural cooperatives have more difficulty in raising large amounts of financial capital for non traditional power generation technology. Additionally, cooperatives have little motivation to innovate as they typically have no competition and are heavily regulated by the government, which makes it difficult to implement any changes. Due to their customer oriented nature, all changes need to substantially benefit customers. Broadband projects in rural areas have typically struggled due to poor rate of return based on a limited user base (NRECA, 2018, 3). PRF enters this sector as a new entrant by showing the benefits of DER in both electricity rate reduction and increased broadband connection. With the successful investment of DER in rural areas, PRF's business model will have utility investment offset broadband investments, which typically have poor rate of return, to aid connectivity projects in this pilot community, a model with potential application to thousands of communities in America.

Specifically in partnering with the Fung Institute of Engineering Leadership, PRF is looking for DER technology with 10 year payback periods, and to help develop load forecasting tools for PIEG. 10 year payback periods were specifically chosen to help make the investments attractive and help support broadband development. Load forecasting is particularly important with renewables due to the variability of the resource, which commonly requires natural gas plants on standby to ramp up to assist with the evening demand period after solar no longer generates.

2. Problem Space

2.1 Landscape of the Current Rural Electric Power Industry

[Author: LC, Reviewer: EF] Utilities can be investor owned, like a traditional company with public stock holdings, and cooperatives, which were formed primarily during the American New Deal to bring utilities to rural areas that were not profitable for investor owned utilities (Davis 1986). These cooperatives would function as limited monopolies in their area of service with rates set by a public utilities commission at the state level. Large utilities such as Pacific Gas and Electric or Tennessee Valley Authority, have their own in-house planning and research divisions to develop future products or they hire engineering or consulting firms (Smart Electric Power Alliance 2017, 8). However, in the case of small rural electric cooperatives the utilities are primarily focused on successful transmission, safe operation and rate management in accordance with state laws. These cooperatives do not have enough staff to develop new projects, nor do they have the investment capital to hire consultants.

2.2 Spurring the Development of Innovative DER

[Author: LC, Reviewer: ZZ] For the utility consulting services that PRF delivers to rural cooperatives, there are no direct competitors. PRF is stepping in to fill the market gap as a non-profit consulting service identifying areas of growth and to drive innovation in their utility infrastructure and providing load forecasting tools for future planning. Communities are especially interested in the PRF because of the potential for broadband infrastructure alongside the development of new energy technologies, which is unique to PRF. In order to feasibly create this infrasture, the PRF builds plans that operate under financial models with 10 year payback periods in order to incentivize outside investment in these projects.

3. Technical Literature Review

[Author: EF, Review: LC] Throughout October the team conducted a thorough literature review of energy technology to determine which technologies were worth pursuing in the target region. The following sections describe solar and wind technology, other alternative energy technologies, and emerging technology in the energy field.

3.1 Solar and Wind Technology

[Author: ZZ, Reviewer:EF] Solar energy technology and photovoltaic (PV) systems were early contenders within the scope of the project because of their widespread availability and ability to serve as a distributed system. PV thrives on supportive policy for renewable energy and improved technology to reduce the cost (Lotker 1991, 1), and the team found that the return on investment for PV installation could range from 4 to about 20 years in the United States, with some states having higher electricity costs and greater support from the government like Massachusetts (Ferroni and others 2017, 498-505). After additional review of several utility-scale PV system operations, the team determined that PV is the most feasible approach for developing DER considering the land availability in MI, the possible cooperation with local customers, and demand for electric compensation.

The team found new wind power systems, especially utility-scale wind farms, would need access to the electric grid to make profits on selling the generation since wind generation is much more random in comparison to solar. The return on investment of wind power system is largely affected by the local average wind speed, ranging from -2% to 13% for a wind turbine with 20-year life cycle (Renewables First 2018). Therefore, investing in wind power requires close cooperation with the government, grid, and investment partners. The team continued to explore this idea, as seen in later sections, because of the availability of information related to wind installations although the costs associated with them are high.

3.2 Other Additional Energy Technologies

[Author: LC, Reviewer: ZZ] Combined heat and power (CHP) uses fuel combustion for electricity and recovers the waste heat to provide hot air and water. CHP additionally pairs well with biomass energy, specifically in burning methane generated from manure. There have been several commercial applications for microturbines for dairy farms where methane is recovered from the manure and burned for heat and electricity (Bioferm 2018). However, when evaluating PIEG's current customer base there did not appear to be any customers that could readily take advantage of this application of biomass or CHP.

Ground source heat pumps and heat electrification use electrical appliances to replace traditional climate conditioning in residences either by replacing gas furnaces with heat pumps or using the ground as a heat sink to reduce climate conditioning requirements (Canadian Center for Housing Technology, 2013). These applications, however, focus on the additional electric load on cooperative's grids, and the team was unable to readily find simulation software to calculate the resource value. Additionally the team decided to focus on technology that would reduce demand peaks by lowering electricity intake by end-users, which would be the opposite of electrification technologies.

3.3 Emerging Technology

[Author: EF, Reviewer: LC] Emerging technologies, like virtual power plants and energy storage systems, were important to the team to consider to ensure that the developed plan was forward thinking. From the National Renewable Energy Lab (NREL)'s paper, which reviewed various types of energy storage, the team decided that battery storage was relevant to the PIEG community, especially when paired with DG, like solar PV systems (U.S. Department Of Energy 2016, 2). However, battery storage is cost-intensive so the team needed to explore optimizing DG before fully pursuing battery storage. The concept of virtual power plants (VPP) was also interesting to the team as it essentially optimizes DG and storage usage across an entire system rather than an entire customer (Zurborg 2018, 2). While enticing, the team recognized before pursuing VPP, DG and storage must be fully investigated.

Following the completion of the October literature review, the team conducted an additional literature review in January pertaining to machine learning (ML) and electric load forecasting. First, the team explored papers that defined different types of ML (Bouktif and others 2018, 3-4). Traditional neural networks could only integrate all the inputs as a whole to generate an output, while a recurrent neural network (RNN) could connect previous information to the present task in the most recent timestep. It is extremely difficult for both networks to connect information from a long-term period (Bengio 1994, 164). However, electric load data usually has patterns across weekly or monthly cycles, indicating that long-term connection of previous information is essential when building the model. Long Short Term Memory (LSTM) RNNs can perfectly solve this problem with its default behavior of remembering information for long periods of time. Jiao et al. (2018) specifically used smaller sets of data similar to the existing data from PIEG to make predictions using LSTM RNNs, which inspired the team to utilize the existing data to create short term prediction networks.

4. Finding and analyzing results

[Author: LC, Reviewer: ZZ] The project team initially attempted to focus on common DER technology with high potentials for rural communities (Krishnaswami, 2018, 3), specifically, residential solar photovoltaics and distributed wind.

4.1 Residential Solar

Residential solar photovoltaics are typically found as rooftop or ground mounted solar panel installations designed primarily to provide additional backup power to residences. Typically, due to size constraints, they are not able to completely power a home, but instead rely on a electrical generation buyback program with the utility for financial compensation.

Distributed Residential Solar was modeled using National Renewable Energy Laboratory's PVWatts calculator. System specifications for array tested included: a 4kW rooftop fixed array, similar to the average solar array size for a single family home in the United States; 16% efficiency, comparable to current technology; 45 degree tilt angle; and 180 degree azimuth. The tilt and azimuth angles were chosen to maximize solar production. For financial parameters, the loan interest was set at 2.5%, no tax credit was applied, and PIEG's electricity rate of $0.115/kWh was applied. Simulations were executed representing 28 different locations based on zip codes within PIEG's area of responsibility. NREL used a synthesized weather data profile based on the last eight years for each locations' latitude and longitude.

	Daily Solar Radiation (kWh/m^2/day)	AC Energy (kWh)	Annual Value
Average	4.368	4961	$570.79
Standard Deviation	0.067	107	$12.43

Table 1. Average Annual Value from 4kW fixed roof array in PIEG's service area

After simulations the team was able to draw two main conclusions. First, Distributed Residential Solar is not currently financially viable in under a 10 year payback period for PIEG's customers. A combination of low solar irradiance and low cost of retail electricity reduces the economic value generated by residential photovoltaic solar. Specifically as shown in Figure 1, Northern Michigan has some of the lowest solar irradiance in the United States ranging in the 3.6 to 4.4 kilowatt-hours per square meter per day. The low radiation is due in part to the higher latitudes and more frequent weather events that make solar more variable. As an additional complication, PIEG's service area has some of the lowest solar irradiance levels in Michigan. Additionally, PIEG has relatively low electric rates compared to other areas of the U.S. due to Michigan's access to natural gas. The low rates, while good for consumers, actually hamper solar payback because they reduce the value of the energy generated from the solar panels. In this simulation, 1:1 net-metering, where PIEG buys back electricity from solar panels at the same retail electric rate, was used to analyze the payback period.

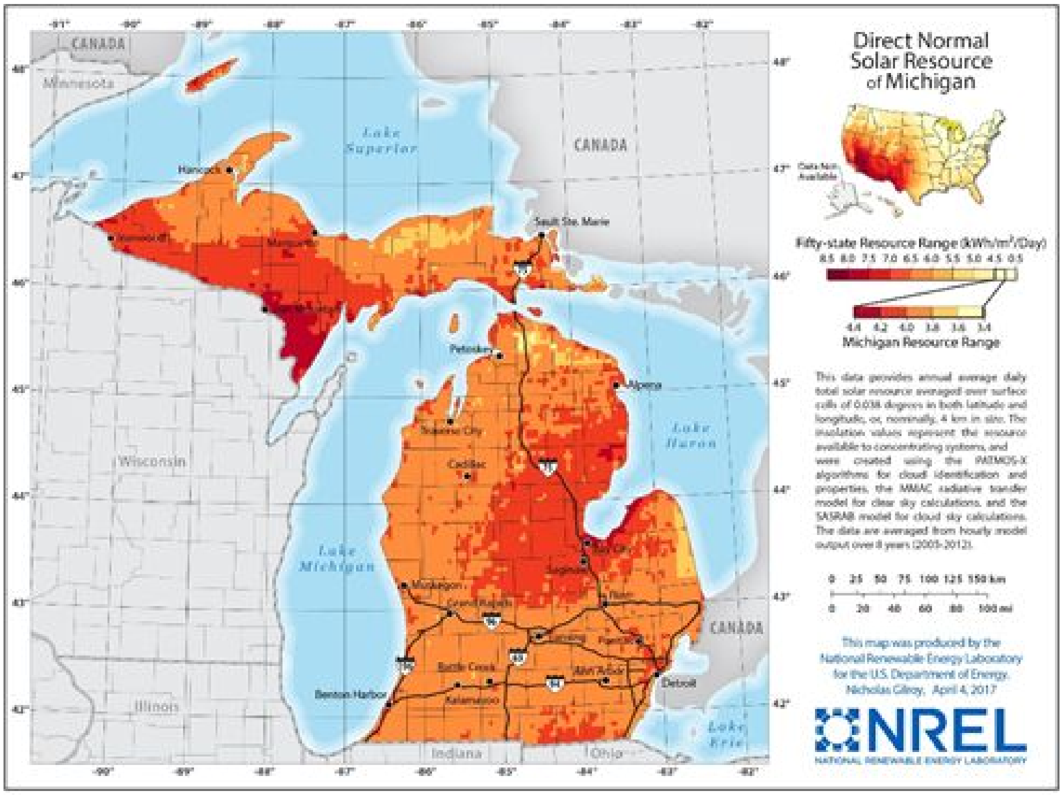

Figure 1. Direct Normal Solar Irradiance for Michigan 1998-2016 (Credit NREL)

However, the team was able to identify a breakpoint where residential solar would become financially viable with 10 year payback periods. This breakpoint would occur when solar installation costs approached $1.25/watt. The current average solar panel installation cost for residential applications is $3.05/watt (Energy Sage, 2018). Commercial applications usually have a cost around $1.25/watt to $1.50/watt, which offers potential for residential customers if prices continue to lower. Historically, installation costs have steadily reduced, however, there is a great deal of uncertainty in the market due to the current tariff on Chinese goods and the future of the federal tax credit for installation (not included in this report's simulation) (Energy Sage, 2018).

4.2 Distributed Wind

Next, the team analyzed distributed wind generation. Similar to residential photovoltaic solar, distributed wind includes small scale wind turbines installed around residential areas and large commercial customers, typically to help offset some utility costs. Commercial wind installations were simulated using System Advisory Model (SAM), Version 2018.11.11, Operating System Windows 10. The wind resource profile was the National Renewable Energies Laboratory (NREL) Eastern Michigan Onshore wind profile set a height of 50 meters. For the simulation four different wind turbines ranging in output from 0.5kW to 25kW were tested with loan periods from 10 to 25 years. PIEG's electrical rates were imported for the financial model, and the Commercial, General Service Three Phase setting was used for all simulations. Default financial parameters were used, except for sales tax which was set at 6% to match Michigan's rate. The payback model included full 1:1 net-metering and no tax incentives.

Turbine	Rating (kW)	Rotor Dia. (M)	Hub Ht. (M)	Loan Period	NPV ($)
Hummer 2.7M	0.5	2	15	25 years	-1,887
Hummer 2.7M	0.5	2	15	10 years	-2,827
Endurance S-343	5	6	15	25 years	-13,520
Endurance S-343	5	6	15	10 years	-17,435
Evoco 9.7M	10	9	15	25 years	-15,722
Evoco 9.7M	10	9	15	10 years	-25,222
Eocycle EO25/12	25	12	20	25 years	-58,344
Eocycle EO25/12	25	12	20	10 years	-84,602

Table 2. SAM Simulation Results with loan periods from 10 to 25 years.

After the simulation, all Net Present Values (NPV) for the wind turbine installations were negative. Larger turbine installations increased the amount of electricity generated and yielded greater profit, however, the overall value of the systems were offset by increasing capital investments. Two issues primarily affected wind generation profitability: lack of wind resource, and PIEG's low electricity rates. The lack of wind resource, shown in Figure 2, reduces the amount of potential electricity generation from wind turbines and overall decreases the rate of payback on the renewable investment. Combining low generation with full 1:1 net-metering to create financial value, distributed wind encountered the same issues as residential solar, namely, low retail costs of electricity reduced the value created by the wind turbines, further making them more difficult to install.

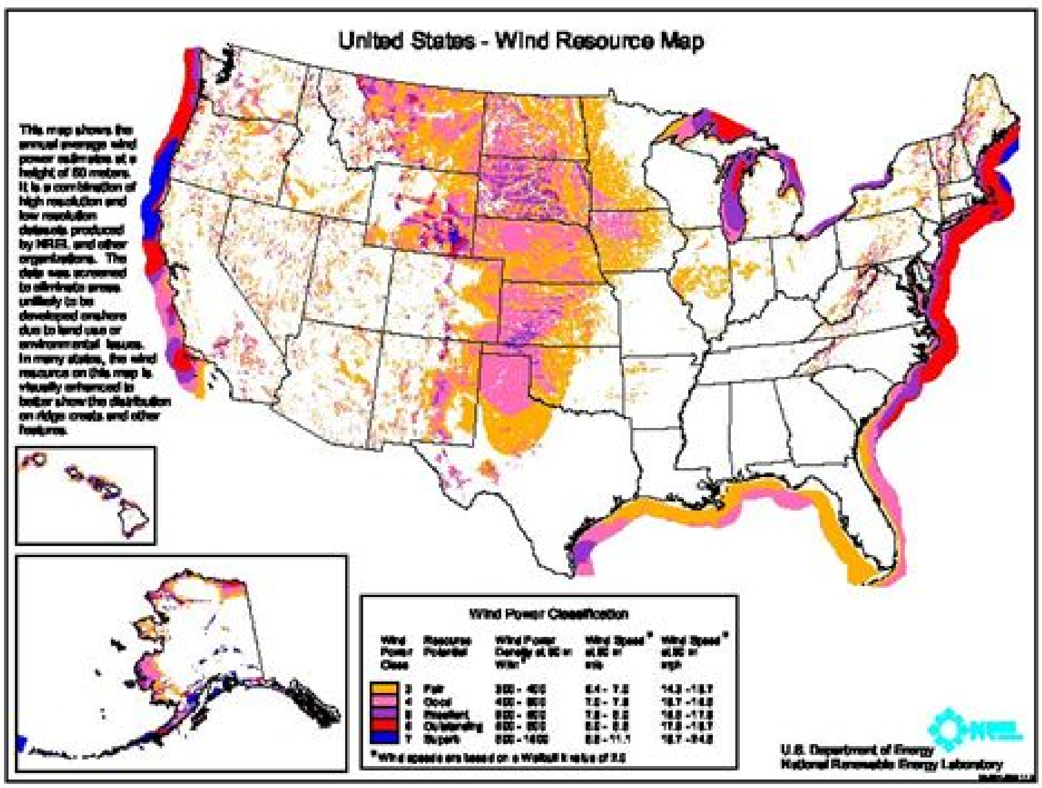

Figure 2. NREL Wind Resource Map. (Credit NREL)

4.3 Commercial Solar

After realizing that distributed residential technologies were not likely to be financially feasible for PIEG, the PRF team instead examined the feasibility of distributed photovoltaic solar for Commercial and Industrial (CNI) customers. The team believed that CNI customers would have a greater potential for success for three reasons, first CNI customers are charged at a peak demand rate, that is they are charged based on the maximum power draw for the month, not their total consumption. This rate structure is due in part that the distributing utility (e.g. PIEG), must install electrical infrastructure able to support that peak power demand. So CNI customers have very high incentives to “load shave”, or reduce their load demands to avoid rate ceilings or extra tariffs, and even small solar arrays can reduce demand peaks. Additionally, CNI customers typically have larger facilities which facilitate larger solar installations, and through an examination of case studies in the Midwest, several CNI solar installations in the 250kW range were proven to be financially viable in Eau Clair, Wisconsin, with a similar latitude as Michigan (NRECA 2018, 12). Finally, unlike residential customers, PIEG was able to supply three months of metering data for their CNI customers. One of the customers, the Alpena Readiness Training Center, actually had a full year of metering data due to Federal Aviation Administration requirements. Based on the data available, the team formulated equations to calculate the projected value of solar installations in a consumption and demand reduction capacity.

4.4 Commercial Solar Optimization Scenarios

While the data was valuable to validate assumptions, in order to balance renewable energy solutions such as solar or wind, some form of energy storage would be required to allow for demand response since natural resources do not generate consistent electricity throughout the entire day. However, energy storage technologies, such as batteries, typically are the most expensive parts of a distributed energy resource installation. The team formulated the following optimization function and constraints based on Moura, 15-03-19, ‘Lecture 8, Case Study: Microgrid Planning and Control,’ in order to properly analyze the trade off between the capital investment costs of solar array systems with energy storage and the return based on reduced electric charges for commercial customers. The variables c_b , c_s, E_{max} , and B_{max} were estimated from Energy Sage’s 2019 report for renewable installation costs and a 2016 report from NREL detailing current available commercial battery storage technology (Mclaren et al. 2016). c_G , c_D , and G_{max} were obtained from PIEG’s 2013 tariff sheet. η_c , η_c were simplified to linear efficiency constraints for ease of program formulation. Finally, S(k) was obtained from NREL's System Advisory Model for the Michigan sites, and L(k) was submitted by the utility. A summary of equations and the variable list are shown in Table 3 and Equations 1-8.

Variable	**Value**	**Units**	**Description**
s, b	Optimize	N/A	Scale factors for the solar and battery array size
S(k)	NREL Data	kW	Power generated from solar
$B_d(k)$, $B_c(k)$	Optimize	kW	Battery Charge and Discharge Power
G(k)	Optimize	kW	Power imported from grid
L(k)	Load data	kW	Power demand of building
E(k)	Optimize	kWh	Energy level of battery
c_b	209	$/kWh	Marginal levelized cost of scaling batt
c_s	2000	$/kW	Marginal levelized cost of scaling solar
c_G	0.07	$/kWh	Cost of grid imported power
c_D	11.06	$/kW	Demand Charge in time
Δt	0.25	hr	Time step
η_c, η_c	0.9	N/A	Battery charge and discharge efficiency
E_{max}	40	kWh	Nominal battery energy capacity
B_{max}	40	kW	Nominal battery power capacity
G_{max}	1961	kW	Maximum grid power
g_d	Varies	kW	Monthly 15 Minute Average of maximum grid import
S_{min} S_{max}	[0,40]		Solar scale limit based on 60 kW arrays
b_{min} b_{max}	[0,20]		Battery scale limits

Table 3. Optimization Notation and Parameter Values, for the Alpena Training Center

$$minimize \quad c_b \cdot b \; + \; c_s \cdot s \; + \; \sum_{k=0}^{N} c_g \cdot G(k) \; + \; c_d \cdot g_d \qquad (1)$$

Equation 1 minimizes the overall capital investment of batteries and solar panels, along with operating costs of importing electricity or operating revenue from exporting electricity, and operating revenue from reduced demand.

This minimization equation is subject to the following equality and inequality constraints:

$$G(k) = L(k) - s \cdot S(k) - B_d(k) + B_c(k) \qquad (2)$$

Equation 2 is the power balance equation, where the energy generated for the solar array, the energy generated from battery discharge, the energy used by battery charge, and the energy from grid import must equal the building's load.

$$E(k+1) = E(k) + \left[\eta_c B_c(k) - \frac{1}{\eta_d} B_d(k)\right] \Delta t \qquad (3)$$

Equation 3 models the battery dynamics via timestep allotting for a discharge and charge efficiency ratio.

$$0 \leq E(k) \leq b \cdot E_{max} \qquad (4)$$

Battery energy limits are modeled by equation 4.

$$0 \leq B_c(k), B_d(k) \leq b \cdot B_{max} \qquad (5)$$

Battery power limits are modeled by equation 5.

$$-G_{max} \leq G(k) \leq G_{max} \qquad (6)$$

The grid power limits is constrained by equation 6. This situation allows for full net-metering.

$$s_{min} \leq s \leq s_{max} \qquad (7)$$

$$b_{min} \leq b \leq b_{max} \qquad (8)$$

Equations 7 and 8 limit the scale of the battery and solar array installation. Based on these equations, the team could optimize the installation of a combined solar and battery array for a commercial customer, based on the historical solar insolation data S(k) for the site, the interval demand data D(k), and the interval load data L(k).

The team then ran simulations for the a regional airport in PIEG's service area. Due to Federal requirements, PIEG was able to supply a full year of demand data, which the team used as a representative yera to predict if solar arrays and batteries would be a feasible distributed energy resource for Commercial customers. MATLAB 2018b, with CVX solver add on, was used on a Windows 10 computer to simulate and the results are summarized below:

Payback Period	**Solar Arrays (60kW)**	**Batteries (40kWh)**
10 Years	None	5
15 Years	None	7
20 Years	4	12

Table 4. Optimized installations by payback period for a regional airport in PIEG's service area.

In these scenarios the Distributed Energy Resources would pay for their installation fees within in the payback period using the savings from reducing the demand and electric consumption charges. The relationship is further shown below, with the peak demand per month shown for the base case, and each optimization period.

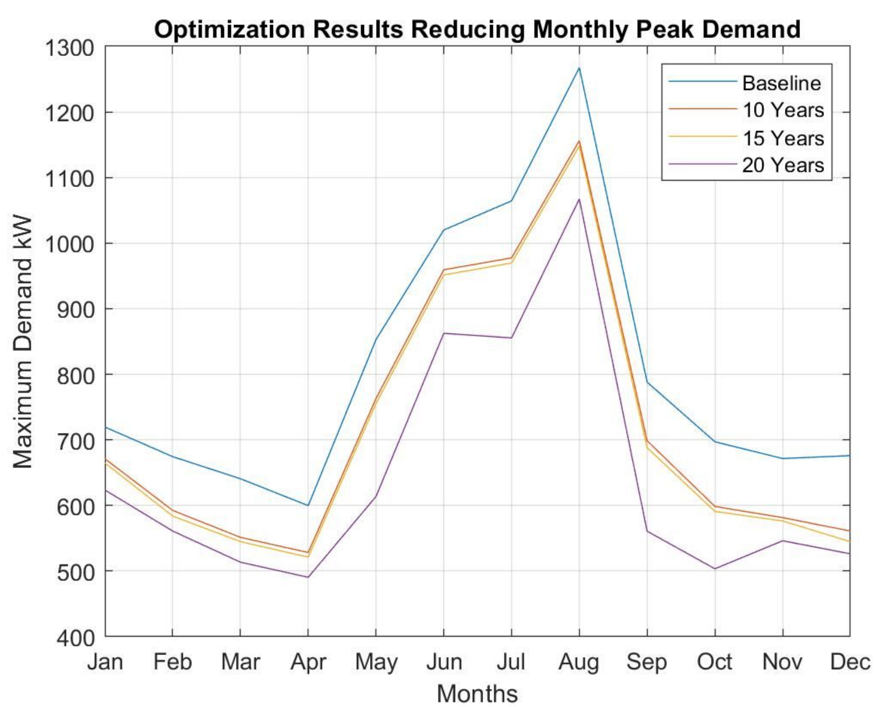

Figure 3. Monthly Demand for the regional airport in base and optimized cases

While this model motivated the team to explore other CNI customers' potential for distributed energy resources, it could also be expanded by adding interest payments in the payback period, and a facilities recapitalization cost e.g. battery replacement at the 10 year mark.

4.5 Electric Load Forecasting Motivation

[Author: LC, Reviewer: EF] After reviewing similar optimization scenarios, the team determined in order to sufficiently design battery and solar array sizes a much larger data set of at least five years of load and demand data was required (Jiao and others 2018, 59443 - 59444). In contrast, PIEG only provided three months of data for eleven of the customers and almost one year of data for the Alpena Training Center. The team realized that the optimization hinged on acquiring a larger dataset to create a representative year and more accurately predict solar array and battery size, and thus pivoted its focus to developing electric load forecasting using machine learning algorithms. These forecasts would then facilitate solar and battery array design, which ultimately allows PRF to forecast loads for PIEG and then make concrete infrastructure investment recommendations.

[Author: EF, Reviewer: LC] In addition to the literature review indicating a higher data requirement for optimization, the team was uncomfortable optimizing only the limited data sets provided by PIEG as there was no way to determine whether or not this optimization would be accurate in the slightest. Considering the dataset provided by PIEG was solely for summer months, when solar irradiance is high, the optimized solution would likely have much smaller PV installations, since less panels would be needed to provide the same level generation, and as a result, be less expensive than an optimization across an entire calendar year. The team felt it was against the mission of this project to provide a potentially infeasible and unreasonable plan to the PIEG community, so we turned our focus towards electric load forecasting as a solution to the data problem.

4.6 Initial Load Forecasting with MATLAB

[Author: ZZ, Reviewer: EF] To develop a commercial solar investment plan, load forecasting plays an essential role in determining the appropriate solar size to install because of inconsistent solar generation. The amount of electricity generated by a solar panel is largely based on the solar irradiance on the panel. So, the daily generation from the solar panel would have a peak at noon and a valley at night. Normally, the electric load curves of CNI customers are relatively flat compared to the solar generation curve, and CNI customers would sell excess electricity generated by solar panels back to the grid to maximize the return of investment from the installed solar panels, which is called net-metering. However, since there is no net-metering in the target community - a self imposed metric to prevent reliance on volatile state and federal policies - the peak generation from solar panels should not exceed the electric loads for each CNI customer to avoid energy waste and interest loss. Here, energy storage could be installed to make full use of excess electricity, but this would be another scenario to analyze. So, assuming no excess electricity is allowed to be generated, accurate prediction of future electric load data is needed to determine the exact amount of solar panels to be installed while maximizing the return of investment.

[Author: EF, Reviewer: LC] The team used the existing PIEG data to create a rudimentary electrical load prediction across all months of 2018 using MATLAB. To do this prediction, the team utilized publically available electricity data from the Energy Information Administration (EIA) for the sector containing Michigan, Illinois, and Ohio. This analysis gave the team a preliminary idea of electrical usage across the year. However, the team recognized there were limitations with this method since the data from PIEG was solely for summer months, which coincides with peak tourism in the area, and using it as the baseline for prediction most likely created a much higher than actual electricity usage prediction for winter months. Within the confines of the problem, if the team sizes optimal PV arrays based on electricity usage that is much greater than it actually is, then surplus generation occurs and net-metering is necessary, which the team is avoiding. In this scenario, underestimating usage is better than overestimating. To address the limitations associated with the MATLAB model, the team explored the possibility of using machine learning to more accurately predict electrical loads.

4.7 Load Forecasting Using Machine Learning

[Author: EF, Reviewer: LC] Electricity usage is highly dependent on previous iterations because systems are limited by how quickly electricity can be produced. As a result, load forecasting is naturally a good candidate for time series based prediction models like a Recurrent Neural Network (RNN). More specifically, the team is using a Long Short Term Memory (LSTM) RNN since this type of model more acutely reduces different types of error propagation that occur in regular RNN. The team built several LSTM RNN using different data sets for training and testing.

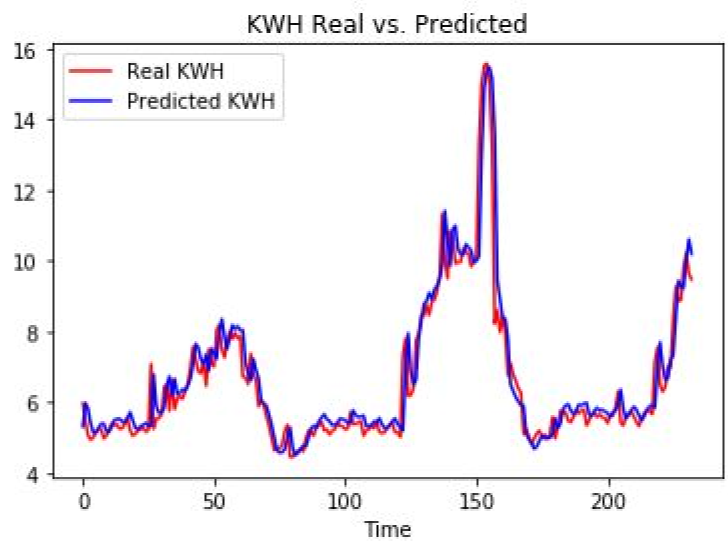

Figure 3. Short Term Model Prediction

The first model developed did short term predictions using the existing PIEG data for training and testing. May, June, and the first three weeks of July were the data sets used for training, while the last week of July was used for testing. The model the team developed was fairly accurate over several hour windows, as shown in Figure 3, and had a mean average percentage error of 5.89% over a four hour prediction window. In the future, this model may be useful when optimizing within the network and running in near-real time. However, the model was limited as it was not capable of predicting across an entire year, which the team needed in order to optimize a PV system. The team also wanted to develop the load forecasting tool to be general enough that it could be applicable to additional communities, but this model was very specific to PIEG.

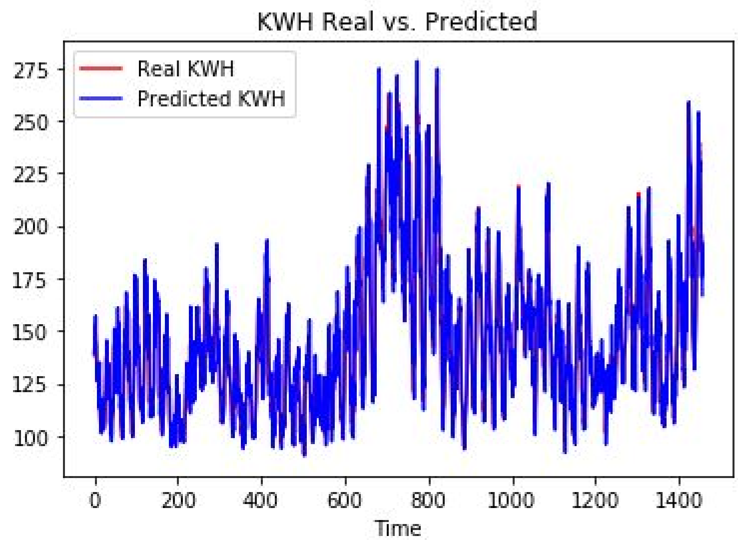

Figure 4. Prediction Using Massachusetts Dataset

[Author: ZZ, Reviewer: EF] Since the team is developing the model to forecast electric load data with parameters like weather and type of industry, at least a full year of training data is needed to ensure accuracy. With the three-month data PIEG provided, the resulting average error for a full-year prediction would be high. Facing this problem, the team decided to look for a full year of electric load data from other sources located in regions with similar altitude and climate as the target community. The team found a full year of electric load data from commercial and industrial facilities in Massachusetts. The team built the LSTM RNN model for regression with standard time steps based on the dataset, and created memory between batches to retain the memory to the next training step so that several data sets from similar industries could train together to create a more general prediction model for a specific industry (Brownlee 2018). The results are shown in Figure 4 and had a mean average percentage error of 11.8%. While this model had potential for being a versatile model, at its crux, it could still only predict several hour windows before the curve converges to an average prediction.

5. Conclusions and Future Research

[Author: ZZ, Reviewer: EF] In this project, the team examined several DER technologies in order to make the best choice of renewable energy for the rural community in North Michigan to adopt. The team eliminated the option of wind power after determining that the net present value of wind power investment is negative even with a 25 year scenario. Residential solar was also ruled out for the reason that Michigan has a relatively low electricity rate that the investment of residential solar would not pay back, and that there is no electric load data for residential sectors available for us to analyze and optimize the size of the panels.

After focusing on commercial solar, the team noticed that investing in commercial and industrial solar systems is the best choice for this rural area to adopt renewable energy. Commercial and industrial customers are charged by the peak usage, so they are incentivized to “load shave”. The team then saw that the limitation of data in rural areas would largely hinder their ability to adopt renewable resources, so the team pivoted and tried to develop a machine learning algorithm to help predict the load data using very limited existing data. Although the algorithm the team built is not reliable for accurate long term prediction of around a year, it still provides resources for future researchers to continue on this study, specifically by expanding parameter selection.

Long-term forecasting for data with complex multivariate analysis is a problem that many data scientists are still trying to solve. Basically, research on long-term forecasting is based on two types of algorithms in machine learning, Deep Neural Networks (DNN) and LSTM RNN. Since electric load is time dependent, time series forecasting using LSTM should be the best option to start with. The reason why the two attempts for long-term forecasting failed is that the team did not input enough features for the look-ahead prediction. Essentially, even if the data set was well trained, the machine could not understand the correlations between the training data and the actual data. However, there is not enough time for the team to build another model to test after figuring out the algorithm.

For future researchers, the team suggests building a LSTM RNN model for this kind of forecasting with multiple layers for different feature inputs that could potentially affect the electric load like temperature, weather, location, month, or even day and then try combinations of different parameters to find the best estimation.

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