EFFECTS OF WIND ENERGY UTILIZATION ON LONG-RUN FUEL CONSUMPTION IN REMOTE ALASKA MICROGRIDS

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Abstract

This paper presents an empirical analysis of the long-run reduction in diesel fuel consumption driven by wind energy utilization in remote Alaska electrical grids. Models control for other fuel consumption determinants including customer base and transmission and distribution system efficiency. Fourteen rural communities that integrated wind energy into their diesel-powered electrical grids are analyzed within a dynamic panel framework using monthly utility data spanning sixteen years, from 2001 to 2017. An auto-regressive distributed lag approach is taken to address cointegration and presence of a unit root in the data. Long-run parameters are estimated for the full dataset as well as for four sub-samples to compare impacts on microgrids with high and low average renewable utilization and with large and small customer bases. Results indicate that fuel consumption is reduced by an estimated 68 gallons on average for each one-percent increase in wind energy penetration on the electricity grid. Beyond 30% average penetration, however, additional wind energy generation leads to increased fuel consumption as turbine curtailment methods must be employed to maintain grid stability, indicating that this is a fuel-offset constraint point in low and medium penetration wind-diesel hybrid systems. High-penetration-capable wind-diesel systems with energy storage capabilities may allow utilities to increase utilization rates beyond this threshold to capture additional fuel savings and carbon emissions offset.

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Abbreviations

AEA	Alaska Energy Authority
ARDL	Autoregressive Distributed Lag
CO_2	carbon dioxide
DFE	dynamic fixed effects
EE&C	energy efficiency & conservation
kWh	kilowatt-hour
MG	mean group
O&M	operations & maintenance
PCE	Power Cost Equalization
PMG	pooled mean group
RE	renewable energy
REF	Renewable Energy Fund

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Introduction

As society has developed, humanity's relationship with energy has transitioned following changing patterns in resource availability, energy demand, and technology. The twenty-first century is seeing a new shift in energy trends as the threat of climate change (Johansson et al, 2012) stimulates technological growth towards large-scale renewable energy utilization and away from proven, yet environmentally costly, fossil fuel technologies. Residents of rural Alaska are particularly familiar with the hazards of a changing climate as the Arctic and sub-Arctic warms at a faster rate than the rest of the planet (Stroeve et al, 2007) and many remote villages are already facing threats – reduced river and sea ice, melting permafrost, changing game migration patterns, stronger storm surges, and coastal erosion (Hamilton et al, 2012) – that are the harbingers of a tumultuous future. Some villages have responded to climate change and high energy costs by developing local energy resources, seeking to save money and contribute to a more sustainable future by offsetting their own fossil fuel use. These pioneering communities provide important case studies for researchers studying small-scale renewable energy generation and integration into remote electrical microgrids.

The economies of rural Alaska communities are primarily resource extraction-based, making them vulnerable to political, regulatory, and environmental shifts in the key industries – petroleum, mining, and commercial fishing (Goldsmith, 2007) – that sustain them. Many communities struggle with limited job opportunities and high rates of unemployment and poverty. In addition, geographic remoteness and high transportation costs result in a high cost of living and a tenuous connection to the urban world and the imported goods it provides. Fuel is one of these imported goods, leading to rural energy costs that can be three to five times higher than in urban areas (Alaska Energy Authority, 2019a) according to the Alaska Energy Authority (AEA), the lead agency for statewide energy policy and program development. Dependency on diesel fuel for electricity and heat leaves communities susceptible to fluctuations in global oil prices and transportation network shocks, plus cash paid to fuel suppliers exits the local economy rather than recirculating. Locally sourced energy can also provide non-monetary benefits such as improved environmental conditions and greater energy security through redundancy in power production methods. These environmental and financial factors present a strong case for shortening the supply chain where possible. Some remote locations, while challenging in many ways, also possess fantastic renewable energy resources in the form of wind, water, or solar for electricity generation.

Over the last decade, the levelized cost of energy[1] for wind power has decreased worldwide by 69% and solar photovoltaic costs have decreased by 88% (Lazard, 2018). With these cost decreases, the economic, logistical, and environmental case for transitioning away from fossil fuels towards local sources of energy is becoming more compelling. Renewable resources can provide energy at a known cost that can hedge against volatile fuel prices and dampen the effects of inflation. Developing sustainable energy sources for electricity generation can save communities[2] millions of dollars each year in the form of displaced fuel and reduced infrastructure capital and operations & maintenance (O&M) costs (Alaska Energy Authority and Renewable Energy Alaska Project, 2019). Critical to these savings, however, is the ability to substantially offset the need for traditional diesel-powered electricity generation. This requires a high-penetration-capable renewable energy (RE) system – one where most of the electricity can be generated by RE during

[1] Levelized cost of energy is a measure that allows comparison of different methods of electricity generation on a consistent basis. It is an economic assessment of the average total cost to build and operate a power-generating asset over its lifetime divided by the total energy output of the asset over that lifetime.
[2] Electricity generation is accomplished on a community-scale while space heating is left to individual building owners. Savings in electricity generation methods, therefore, accrue to the community as a whole, via the utility.

times of high resource availability – that maintains the essential features of reliability and stability that characterize existing diesel generation technology.

To investigate the connection between renewable energy utilization and the use of diesel fuel (the costliest input to traditional generation in terms of financial and environmental impact), data from 14 rural Alaska communities that supplemented their electrical generation systems with wind energy at various points during a sixteen-year timespan is analyzed. These communities were pioneers in wind-diesel microgrid system integration; now, nearly a decade later, data is available to estimate the long-run effects that these projects have had on fuel use. A panel approach is used to control for community-specific effects as the communities vary in terms of their size, location, and electrical grid characteristics. This analysis draws on methods developed by Pesaran, Shin, and Smith (1999) to estimate long-run relationships between fuel consumption and renewable energy utilization rate, customer base, and system efficiency using a panel autoregressive distributed lag (ARDL) approach. The remainder of this paper is as follows: background information on rural Alaska microgrids, technical limitations to integrating high-penetration renewable energy systems, and the basics of wind energy systems; overview of estimation methods for nonstationary heterogeneous panels; review of the data; presentation and discussion of econometric results; commentary on system requirements for maximizing fuel savings; limitations of the analysis; and finally, conclusions and suggestions for further research.

Background Information

Rural Arctic and sub-Arctic Alaska is majority Alaska Native in population and has been inhabited for thousands of years; enduring communities exist at locations that have long been favorable for hunting or fishing (Hamilton et al, 2012). Subsistence harvesting of meat, fish, and plants coexists with the cash economy in many communities, providing an important cultural link while also supplementing diets where purchased food can cost five times more than in Anchorage (Loring and Gerlach, 2009). One-quarter of the state's population lives in remote communities that are disconnected from each other and from the main road system that links the urban hubs of Anchorage and Fairbanks to each other and to the rest of the continent (Melendez & Fay, 2012). Higher population communities such as Utqiagvik (Barrow), Nome, Kotzebue, Bethel, Dillingham, and Unalaska are regional hubs for transportation, economic activity, and services in rural Alaska. Peppered around the hub communities, villages replicate basic services on a smaller scale, each providing standalone electric, transportation, and other services that are very expensive with infrastructure costs spread among fewer customers.

Many villages are only accessible year-round by air; the ice-free months of summer also allow for water access for most. Due to the high cost of air freight, most goods, including fuel, are delivered to rural villages by barge. Diesel fuel provides most rural utilities' electricity needs, powering large diesel-electric generators in centralized power plants. These "microgrids" are self-contained, islanded systems that must produce all electricity locally. Sourced from outside the community, diesel fuel is ordered in bulk during the summer and stored in fuel tank farms for use throughout the year. After freeze-up, utilities rely on this stored fuel for electricity generation or pay a premium to fly fuel in by air tanker (AEA & REAP, 2016). This fuel transportation network exposes communities and the surrounding natural environment to risks of fuel spills and contamination given extreme weather conditions and limited logistical support and emergency services available between population hubs.

Most renewable energy projects in Alaska were developed with financial assistance from federal or state funding sources (or a combination of both) including the U.S. Department of

Energy, the U.S. Department of Agriculture, the Denali Commission[3], and the state of Alaska's Renewable Energy Fund (REF). Created by the Alaska Legislature in 2008 and administered by the Alaska Energy Authority, the REF grant program was a major stimulus for renewable energy projects in the state, funding or partially funding the construction or further development of nearly 80 electrical and/or heat projects, including eleven of the projects in this analysis[4] (AEA, 2019d). REF grants were often combined with other funding sources and were awarded for reconnaissance, feasibility studies, and construction projects.

The REF scoring guidelines reflected the thinking of the state's leading energy experts at the time regarding renewable integration in rural microgrids. Applicant projects were evaluated by AEA staff and scored based on eligibility, technical and economic feasibility, current cost of energy in the community, local support, matching funding, and experience and qualifications of the applicant (AEA, 2019d). The technical and economic evaluations were conducted by a team of technical reviewers and independent economists. The economic cost-benefit analysis considered project capital costs, expected lifespan, displaced diesel-generated electrical energy or heat, operations and maintenance (O&M) costs, projected fuel prices, and avoided carbon dioxide (CO_2) emissions (AEA, 2015).

The REF economic analysis required that projects be classified as diesels-on or diesels-off (AEA, 2015). Diesels-on referred to projects where the diesel-electric generators would continue to operate while renewable(s) are producing power. Most project applications submitted to the REF fell into this category. For these projects, AEA assumed zero change in the O&M costs

[3] The Denali Commission is an independent federal agency designed to provide critical utilities, infrastructure, and economic support throughout Alaska, with a focus on remote communities.
[4] While the REF is still an active AEA program, the Alaska Legislature has not allocated new funding since 2016 due to declines in state revenue. AEA has made awards in the years since but is not accepting new applications.

associated with operating the diesel portion of the powerhouse. Diesels-off referred to projects where the base diesel powerhouse would be turned off while the renewable(s) are producing power. For these projects, AEA assumed savings from reductions in diesel O&M costs associated with reducing the hours of operation. Typically, hydroelectric projects were the only projects that were classified as diesels-off capable. Both classifications assumed an estimated fuel displacement. AEA's assumption of zero change in diesel O&M costs for diesels-on projects (which included all wind projects) is simple yet profound: reductions in diesel generator usage are assumed to be limited, indicating that financial savings may be constrained.

Diesel generation O&M costs include oil, oil filters, and parts and labor costs associated with periodic engine overhauls. These O&M costs are required at specific operating time intervals: after 10,000 hours of run-time, for example. Overhaul intervals do not change based on the engine speed of operation – an hour is an hour. Only renewable energy projects with diesels-off capability will decrease these costs by reducing net operating hours. Diesel-electric generators are most efficient when operated at or around 80% of their rated capacity; this is the point at which O&M costs are minimized. At engine speeds above and below[5] this optimum, generators become more expensive to operate with higher O&M costs per kWh produced and shortened service cycles due to increased wear (Vaught, personal interview, 2019).

Renewable Integration into Remote Microgrids

Renewable energy systems are categorized in terms of their average penetration levels, or the overall proportion of RE-generated electricity compared to total generation (RE + diesel):

[5] Operating below 30% of their capacity for extended time periods has negative impacts on diesel generators including "wet stacking", a condition resulting from unburned fuel that passes into the exhaust system, as well as the buildup of deposits behind piston rings and inside the cylinders, also as a result of unburned fuel (Lockard, 2019).

$$Average\ Penetration = \frac{Renewable\ energy\ generation\ (RE)}{Total\ energy\ generation\ (RE{+}diesel)} \tag{1}$$

In this analysis, average wind penetration is interpreted in per-month terms. Higher-penetration renewable energy systems can offset significant diesel-generation costs when properly configured. Achieving high wind penetration levels is challenging, however, because electricity is difficult to store and because supply and demand must remain in balance in order to ensure system reliability (International Energy Agency-Renewable Energy Technology Deployment, 2012). Integrating renewables into rural microgrids requires a thorough understanding of local infrastructure such as the characteristics of the electricity load[6] and the condition of the existing electrical equipment.

Energy systems are sized and optimized to meet the overall load, and significant changes in load demand that occur after construction can result in an RE system that is oversized or undersized for the load. Potential load changes include seasonal changes in demand, where primary economic drivers like commercial fishing in coastal Alaskan communities can lead to large summer demand spikes, and overall demand growth or decline due to population changes or changes in customer base make-up. In small electrical grids, individual customers that consume large amounts of energy such as schools or industrial users can drive the load and the infrastructure capacity required to handle demand peaks. In very small communities, the closure of a school due to below-minimum enrollment or the loss of a large commercial customer can drastically reduce overall energy demand. It can be challenging for large capacity grids to efficiently serve the electrical load if this happens, as diesel generators sized for a larger load perform poorly at low operating levels (Baring-Gould & Corbus, 2007). Before renewable integration, a community

[6] Load is the amount of electricity on the grid at any given time as it travels from the power plant to end users.

electrical system should include differently sized generators to accommodate load fluctuations due to both cyclical and lasting demand changes. This analysis accounts for changes in customer base as a determinant of energy demand and, subsequently, fuel consumption.

To properly integrate renewable energy technologies, the existing electrical generation equipment – generators, control systems, and transmission and distribution equipment – may require modifications to be able to handle intermittent renewable energy (IEA-RETD, 2012). In RE-diesel hybrid systems that are not diesels-off capable, diesel generators must be able to throttle down to accommodate periods of high renewable generation. Rural utilities that have older diesel engines that cannot respond quickly would need to retrofit throttle controls or replace the engines themselves before adding renewables. Transmission and distribution equipment that is oversized, poorly maintained, or that experiences electrical losses (called line loss) of 20% or higher would reduce the fuel-saving effects of renewable energy if not addressed. Line loss is the difference between the electricity generated (from all sources) and the electricity sold plus that consumed in powerhouse operations. Some line loss is inevitable[7] but high amounts of loss represent wasted fuel and renewable-generated electricity. Line loss is included in this analysis as a measure of system efficiency.

The term electricity generator can refer to a traditional diesel-powered generator (also called a diesel engine) or a renewable-powered generator such as wind or hydro. The three types of electricity generators are base load, dispatchable, and intermittent. *Base load* generators produce electricity at a single output level and are poorly suited to respond to rapid changes in load demand. They cannot be easily turned on and off and hence are unsuitable to support the integration of other

[7] Called the Joule heating effect, the energy of an electric current is converted to heat as it flows through a resistance and some of this heat is lost to the atmosphere along the transmission and distribution system (Schonek, 2013).

types of renewable energy. An example of this is geothermal power. *Dispatchable* generators are designed to vary their power output and can be turned on and off as needed to meet demand. Diesel generators are dispatchable, as is traditional hydropower (water impounded behind a dam) because the output from the reservoir can be adjusted to meet load demand. Because of the ability to control generation output, communities with a dispatchable renewable resource can achieve 100% renewable penetration with relative ease. In contrast, *intermittent* generators cannot always reliably provide power. These include solar energy, which is diurnal and susceptible to interruptions from cloud cover, and wind energy, which is stochastic.

Intermittent generation can be integrated easily into remote microgrids at low penetration levels because the output is small relative to diesel generation, but achieving higher penetration requires more sophisticated control technologies and storage. Increases in the amount of base load or dispatchable renewable energy feeding onto the grid can positively impact grid reliability but increases in the amount of intermittent renewable energy can have a negative impact if not properly planned for and managed (IEA-RETD, 2012).

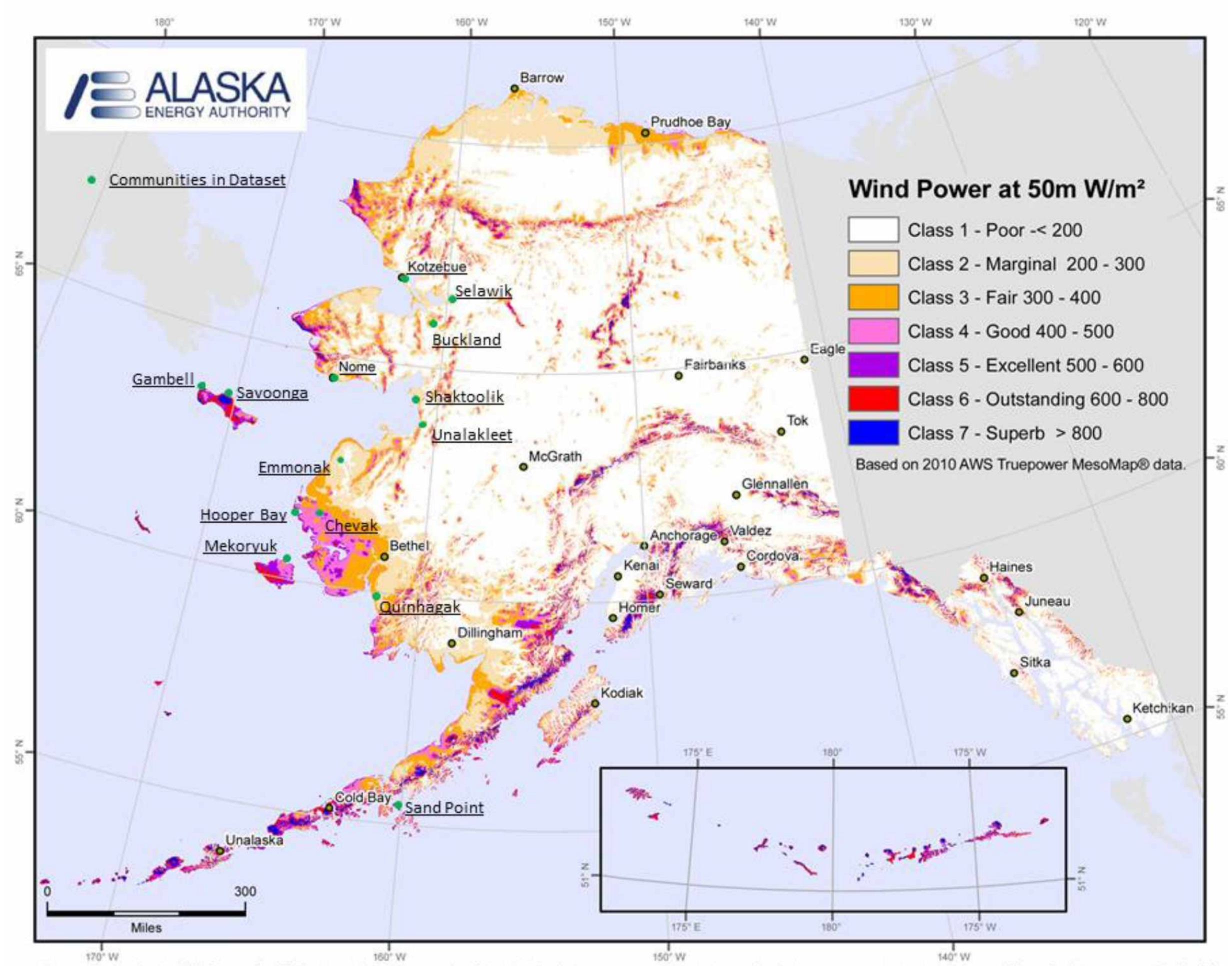
Wind Energy Basics

The communities analyzed in this paper are scattered across three sub-regions of Alaska: eight are in the Arctic northwest, three in the Yukon-Kuskokwim Delta, and three in the southwest. Fig. 1 shows the communities in the dataset on a wind resource map which classifies wind energy potential[8]. Most of the communities that have developed wind projects in Alaska are in western Alaska, the general geographic area south of the Brooks Range and north of the Yukon-Kuskokwim River Delta. Defined by its flat, featureless terrain, western Alaska is very favorable

[8] Fig. 1 shows the estimated wind resource across the state, but strength and quality are very site-specific, so it is critical to measure the local wind resource when considering project development.

for wind development because it has strong onshore winds that sweep straight across the land. The lack of significant vegetation results in optimal wind flow conditions that exhibit very low turbulence and produce an energy resource that is easier to harness. In addition to its consistent wind, western Alaska has seen considerable project development because it has many villages with relatively large populations, allowing for better scalability and capture of efficiencies in terms of similar project designs, development, and logistics. Natural clustering also means that some villages can be connected by transmission intertie, enabling the development of larger renewable projects and allowing for fixed costs to be spread across more customers.

Figure 1. *Map of communities included in analysis.*



Source: Alaska Energy Authority.

Wind-diesel power system configurations are categorized based on their average penetration levels. See Table 1 for additional explanation. The actual division between penetration levels varies between systems and depends on the ability of diesel generators to manage the stochastic energy produced by wind turbines. The Alaska Energy Authority categorizes wind-diesel penetration levels as very low, low, medium, and high. The categories roughly equate to the amount of diesel fuel displaced by wind power.

Table 1*. AEA categories of wind-diesel system configuration.*

Penetration Category	Average Wind Penetration Level	Operating Characteristics and System Requirements
Very Low	<8%	• Diesel generators run full time • Wind power reduces net load on diesel • All wind energy serves primary load • No supervisory control system needed
Low	8-20%	• Diesel generators run full time • Secondary loads or wind turbine curtailment required to ensure sufficient diesel loading • Relatively simple supervisory control system
Medium	20-50%	• Diesel generators run full time • Secondary loads required to ensure sufficient diesel loading • Sophisticated supervisory control system
High (Diesels-off Capable)	50-100%	• Diesels-off capability • Energy storage may be required • Highly sophisticated supervisory control system

Source: V3 Energy, 2018

At low penetration levels (8% to 20%), diesel generators can automatically adjust to accommodate renewable generation; at medium penetration levels (20% to 50%) it becomes more important to have several sizes of diesel engines to choose from based on input mix. Many rural Alaska microgrids were designed with redundancy in mind rather than for renewable integration capability, and so do not have the engine size variety or small enough engines to properly accommodate the renewable input and operate at an ideal power output. Power plants tend to have at least one smaller diesel generator to use during the summer when overall electricity demand is lower (more daylight, warmer temperatures, and school is out of session) and one larger diesel generator to use during winter when demand is high. Utilities often also have a second large generator for redundancy in case the primary large generator is down during winter months, as the summer generator would not be large enough to handle the winter load. Utilities install a one-small, two-large configuration instead of a two-small, one-large configuration because running two small generators in parallel to produce equivalent power as one large generator requires a much higher level of training and understanding by powerplant operators (Vaught, personal interview, 2019). This common composition of existing assets in many rural microgrids is important to note as it impacts the level of wind energy generation that can be utilized in a system. Medium penetration is the type of system configuration in most Alaska village wind-diesel systems, including most developed through the REF, as it has commonly been considered a good compromise between fuel use offset and relatively minimal system complexity. Medium penetration has proven difficult to manage in practice, however, as it combines high instantaneous wind input with a control strategy that is not always sufficient to manage the process (V3 Energy, 2018). Some of the challenges of early Alaska village wind energy projects reflect an initial lack of understanding of the importance of system integration techniques to handle higher amounts of wind penetration.

To maintain stability, systems such as curtailment (the ability to reduce wind turbine power output), thermal loads, or energy storage may be necessary. The need for control systems occurs on the margins, or extremes, of wind output potential. In cases of wind power production that exceeds power demand, control elements must be implemented to avoid system instability. Turbine curtailment is a common strategy as it is relatively easy – turbine blades are angled out of the wind or shut down altogether[9] – but it underutilizes the renewable resource (V3 Energy, 2018). Thermal loads such as electric stoves are a better option than curtailment because they use excess wind power to offset traditional heating fuel in large buildings like schools or hospitals rather than wasting it.

Properly configured high penetration wind-diesel systems that provide the potential to shut down the diesel powerhouse completely during periods of high wind output provide the most substantial fuel savings. To ensure system reliability and avoid power outages, a considerable amount of short-term energy storage is required to bridge a sudden decline in wind availability with diesel generator start-up. The wind-diesel hybrid systems analyzed in this paper do not include energy storage capabilities for the years modeled and hence only demonstrate the upper limits of fuel offset in low and medium penetration systems.

In recognition of the limitations of medium penetration wind configurations, the wind-diesel categories are often collapsed to just two – low and high – that reflect the essential interactions between the wind and diesel sides of the system (see Table 2). At low penetration, wind turbine power generation is not enough to influence power quality and diesel operations, so minimal control measures are needed. At high penetration, wind turbine integration requires sophisticated control measures because it has the potential to significantly impact power quality and diesel engine loading.

[9] Variable pitch turbine blades can be angled out of the wind to generate less electricity as a curtailment method; fixed pitch turbine blades cannot and hence these turbines must be shut down to be curtailed.

Table 2*. Revised categories of wind-diesel system configuration.*

Penetration Category	Average Wind Penetration Level	Operating Characteristics and System Requirements
Low	8-20%	• Diesel generators run full time • Secondary loads or wind turbine curtailment required to ensure sufficient diesel loading • Relatively simple control system needed
High (Diesels-off capable)	50-100%	• Diesels-off capability • Energy storage may be required • Highly sophisticated control system needed

Source: V3 Energy, 2018

Pre-Estimation Review of Dataset

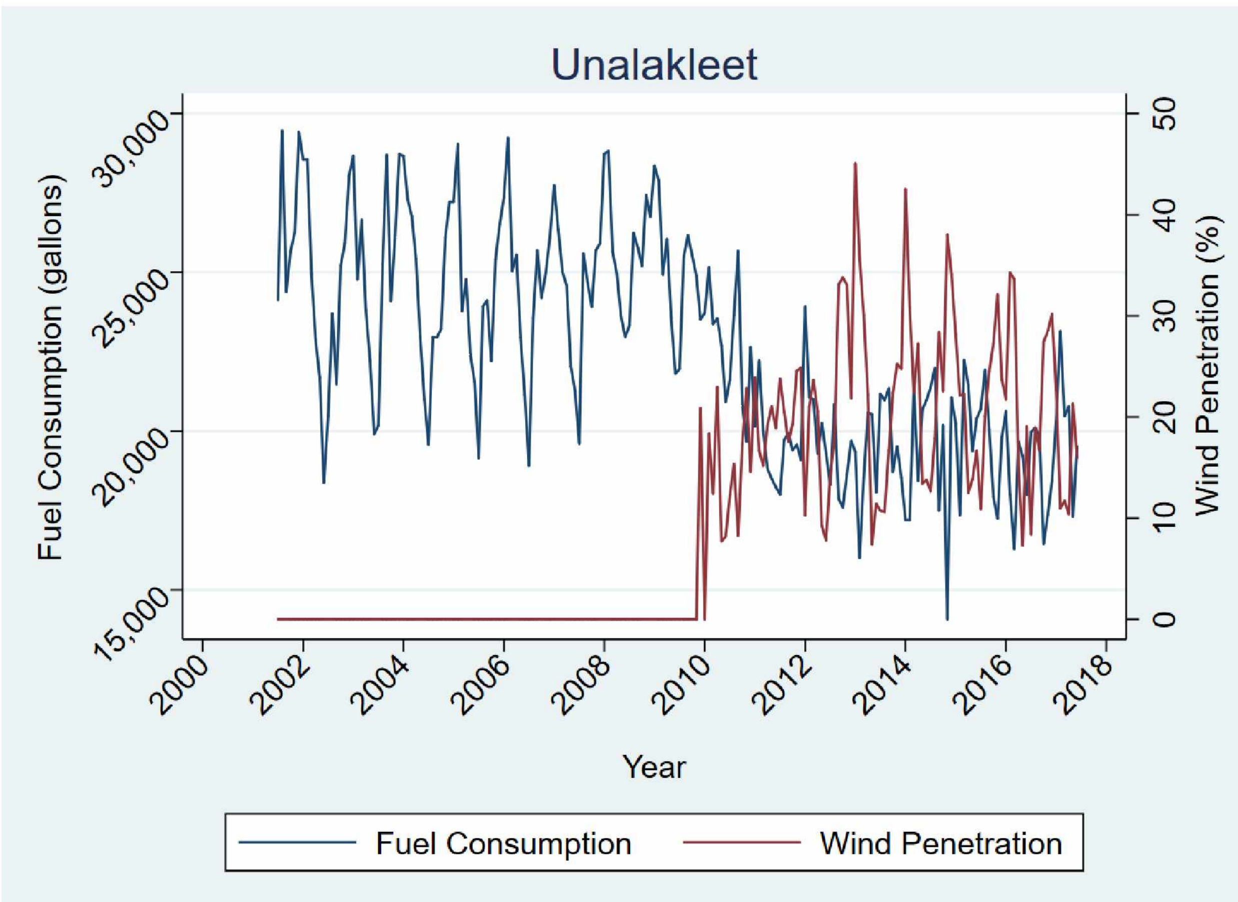
Based on categories listed in Table 1, the communities included in this analysis vary in terms of their wind-diesel system configurations and penetration levels, ranging from a very low average penetration of 3.85% in Selawik to a medium average penetration of 29.93% in Chevak (see Table 3 for wind penetration statistics). Monthly average penetration levels vary between a low of effectively zero and a high of nearly 70 percent.

Table 3. *Wind penetration statistics, excluding months with no wind generation.*

	Average monthly wind penetration		
	Mean	Min	Max
Buckland	8.24%	0.34%	18.85%
Chevak	29.93%	0.07%	69.90%
Emmonak	12.54%	0.00%	34.40%
Gambell	23.26%	1.01%	50.65%
Hooper Bay	15.80%	0.55%	49.00%
Kotzebue	9.73%	0.07%	35.30%
Mekoryuk	19.23%	0.01%	42.15%
Nome	4.15%	0.99%	13.47%
Quinhagak	24.79%	9.17%	46.66%
Sand Point	20.28%	0.29%	38.89%
Savoonga	13.65%	0.01%	37.42%
Selawik	3.85%	0.00%	16.51%
Shaktoolik	28.15%	0.12%	57.64%
Unalakleet	20.53%	7.33%	45.06%

Graphical depiction of diesel fuel usage and average wind penetration suggest a significant negative relationship between the two variables. See Figure 2 for a plot of fuel consumption and wind penetration over time for the community of Unalakleet. In this illustrative example, a noticeable decline in fuel use in conjunction with the integration of wind energy in the community in 2010 provides a striking visual indication of significant renewable-driven fuel reductions. This reduction is formally estimated using a panel ARDL model as described in the methodology section that follows.

Figure 2. *Plot of generator fuel consumption against wind penetration for Unalakleet.*



From inspection it is easy to see the extreme seasonality in diesel fuel consumption patterns resulting from the dramatic reduction of electrical load demand due to daylight availability and temperature as well as the reduction of energy usage at the school, a large user, during summer months. The wind resource varies on a seasonal basis and is stronger during winter months due to larger temperature gradients between low and high latitudes (North Carolina Climate Office, n.d.).

Extreme seasonality indicates potential non-stationarity of the data, leading to consideration of the mean group (MG) (Pesaran and Smith, 1995) and the pooled mean group (PMG) (Pesaran, Shin, and Smith 1997, 1999) estimation techniques given their treatment of nonstationary heterogeneous panels. Based on the direction taken by Baek and Choi (2017) in a similar dynamic panel analysis, the pooled mean group (PMG) estimator is expected to be more applicable than traditional panel methods because it allows short-run dynamics to differ across communities while constraining long-run relationships to behave identically. The communities in the dataset possess significant heterogeneity in terms of population size, system configuration, resource strength and availability, and load characteristics, and long-run parameters of the PMG estimator are anticipated to be less prone to the influence of outliers in the data.

This analysis is the first that uses an autoregressive distributed lag approach to estimate long-run parameters for wind-energy-induced fossil fuel consumption reductions at the microgrid level. Two studies are found that are similar in topic but not in method or scale: Thomson, Harrison, and Chick (2017) study historical data from Great Britain to isolate the marginal emissions displacement of wind power, but this country-level approach is limited in its applicability to islanded microgrids; and Cabrera, Lund, and Carta (2018) apply a unique procedure to identify the optimum configuration of renewable installations on the island of Gran Canaria to increase the share of RE penetration, but their focus is on *potential* fossil fuel savings under various scenarios rather than *actual* savings from existing configurations.

Methodology

To isolate the independent effect of wind energy penetration level on powerhouse diesel fuel consumption, a dynamic panel equation is estimated following direction taken by Baek and Choi (2017) with wind penetration in quadratic form and controlling for two additional determinants. The long-run form of the equation is specified as follows:

$$gen\_fuel_{it} = \beta_0 + \beta_1 wind\_pen_{it} + \beta_2 wind\_pen^2_{it} + \beta_3 num\_total\_cust_{it} + \beta_4 line\_loss_{it} + u_t \tag{2}$$

where gen_fuel_{it} is gallons of diesel fuel used for electricity generation in period t for community i (denoted by the subscript '$_{it}$'); $wind\_pen_{it}$ is average wind penetration; $num\_total\_cust_{it}$ is the customer base; $line\_loss_{it}$ is the line loss rate; β_0 is a constant, $\beta_{1\text{-}4}$ are estimated coefficients, and u_t is the error term. In Equation (2), the coefficient on $wind\_pen_{it}$ is expected to be negative, consistent with the hypothesis that increasing electrical energy generation from renewable sources decreases the need for diesel-generated energy and, therefore, decreases diesel fuel consumption. The relationship between *wind_pen* and *gen_fuel* is expected to be non-linear as increases in penetration level at low levels are known to have differing effects on the grid than at higher levels (V3 Energy, 2018), so the penetration variable is included in quadratic form. The coefficient on $wind\_pen^2_{it}$ is expected to be positive indicating that the quadratic has a parabolic shape: wind penetration is likely to have a diminishing effect on *gen_fuel* above certain average utilization levels. A population-driven increase (decrease) in total demand for electricity is expected to increase (decrease) demand for fuel, so the coefficient on $num\_total\_cust_{it}$ is expected to be positive. Finally, the coefficient on $line\_loss_{it}$ is expected to be positive as higher rates of line loss indicate greater system inefficiencies, requiring more diesel fuel and renewable energy to generate electricity than more efficient systems.

Given system interactions and interdependency, a difference-stationary approach using an autoregressive distributed lag (1,1,1,1) shown in Equation (3) is determined to be the best model for analysis (Pesaran et al., 1999). The ARDL model includes lags of both the dependent variable and the independent variables, an approach that addresses non-stationarity in the data, including extreme seasonality. The model can also handle mixed integration time series, should a unit root be present in the data.

$$\begin{aligned} gen\_fuel_{it} = {} & \mu_t + \delta_{10i}wind\_pen_{it} + \delta_{11i}wind\_pen_{i,t-1} + \delta_{20i}wind\_pen^2_{it} + \delta_{21i}wind\_pen^2_{i,t-1} + \\ & \delta_{30i}num\_total\_cust_{it} + \delta_{31i}num\_total\_cust_{i,t-1} + \delta_{40i}line\_loss_{it} + \delta_{41i}line\_loss_{i,t-1} + \\ & \lambda_i gen\_fuel_{i,t-1} + u_t \end{aligned} \tag{3}$$

If the variables are also cointegrated, however, then (3) can be reparametrized into an error correction modeling format in order to add back in valuable long-run information lost in the ARDL process:

$$\begin{aligned} \Delta gen\_fuel_{it} = {} & \Phi_i(gen\_fuel_{i,t-1} - \alpha_{0i} - \alpha_{1i}wind\_pen_{it} - \alpha_{2i}wind\_pen^2_{it} - \alpha_{3i}num\_total\_cust_{it} - \\ & {}_{4i}line\_loss_{it}) - \delta_{11i}\Delta wind\_pen_{it} - \delta_{21i}\Delta wind\_pen^2_{it} - \delta_{31i}\Delta num\_total\_cust_{it} - \\ & \delta_{41i}\Delta line\_loss_{it} - \varepsilon_{it} \end{aligned} \tag{4}$$

where,

$$\Phi_i = -(1 - \lambda_i);\ \alpha_{0i} = \frac{\mu_t}{1 - \lambda_i};\ \alpha_{1i} = \frac{\delta_{10i} + \delta_{11i}}{1 - \lambda_i};\ \alpha_{2i} = \frac{\delta_{20i} + \delta_{21i}}{1 - \lambda_i};\ \alpha_{3i} = \frac{\delta_{30i} + \delta_{31i}}{1 - \lambda_i};\ \alpha_{4i} = \frac{\delta_{40i} + \delta_{41i}}{1 - \lambda_i}$$

In Equation (4), α_{it} represents the long-run relationship between dependent variable gen_fuel_{it} and its determinant independent variables; δ_{it} represents the short-run coefficients. The long-run relationships are captured in the first half of the equation where they are multiplied by the error correction term, and the short-run relationships are captured in the second half. The error correction term (EC), represented by Φ_i, indicates the response rate of gen_fuel_{it} to recover to long-run equilibrium following a "shock", or a change in one of its determinants. A negative and highly significant error correction term is a sign of a cointegration relationship among the variables. By estimating Φ_i, the error correction model format restores the long-run cointegration relationship between the dependent and independent variables that was removed through the ARDL difference-stationary process. Equation (4) includes the lagged dependent variable because it may take time for changes to take effect in the long-run model.

Given the dynamic nature of the panel data, three alternative estimation methods are applied to check for best fit. Equation (4) is estimated using the mean group (MG), dynamic fixed effects (DFE), and pooled mean group (PMG) estimators. As noted by Pesaran and Smith (1995), the MG method estimates are the unweighted averages of the estimated coefficients from separate time series regressions, as MG does not impose homogeneity restrictions on parameters across panels. It allows intercepts, short- and long-run parameters, and errors variances all to be heterogeneous across communities. The DFE method pools the time series data for each group, allowing the intercepts to be heterogenous across communities but constraining the short- and long-run parameters and error variances to be equal. The PMG estimator is known as an intermediate estimator between the two methods, relying on a combination of pooling and averaging and allowing short-run parameters, intercepts, and error variances to vary across communities but constraining long-run parameters to be equal (Blackburne and Frank, 2007).

Data

The data used in this analysis is sourced from AEA's Power Cost Equalization (PCE) dataset, accessed via the Alaska Energy Data Gateway[10] online portal in January 2019 (AEA,

[10] Alaska Energy Data Gateway, developed by the Institute of Social and Economic Research, University of Alaska Anchorage, is supported by the U.S. Department of Energy (DOE), Office of Science, Basic Energy Sciences (BES),

2019a). This data is self-reported to AEA by utilities as a monthly requirement for participation in the PCE program, a rural electricity assistance program that subsidizes electricity rates for residential customers and community facilities to help ensure the viability of the local utility given extremely high costs of rural electricity generation. AEA shares community-level electricity cost, consumption, and generation data with the public for use in education and research. Because the PCE data is self-reported, the original dataset contained errors and inconsistencies that had to be addressed before use. Additionally, the dataset utilized in this analysis includes "uncleaned" years, meaning that observations from years 2015-2017 have not been reviewed and cleaned by AEA to meet AEDG data quality standards.

Equation (4) is estimated using a panel of fourteen rural Alaska communities that each integrated wind turbines into their power systems at various points during the time frame analyzed. The time series is monthly spanning July 2001 to June 2017. The dataset contains a balanced panel of 2,688 observations (N=14 wind communities and T=192 months). Data points are interpreted as per-month values: the dependent variable *gen_fuel* refers to gallons of diesel fuel used for electricity generation in the utility powerhouse; *wind_pen* is average wind penetration, calculated by dividing monthly wind energy generated by total energy generated[11], which is the sum of the energy generated (in kWh) from both wind and diesel; *num_total_cust* represents the number of electricity customer accounts which is made up of residential, commercial, community, government, and unbilled customers; and *line_loss* is the percentage of electricity generated by the utility that is lost due to transmission and distribution system inefficiencies. This is calculated by

under EPSCoR Award #DE-SC0004903 (database and web application development), and by Alaska Energy Authority (Renewable Energy Fund data management and reporting). Database and web hosting is provided by the Institute of Social and Economic Research, University of Alaska Anchorage.

[11] By including total energy generated, the wind penetration variable holds market demand constant. Wind-driven diesel fuel displacement is therefore conditional on the overall load.

subtracting powerhouse consumption and total energy sold (or consumed by unbilled customers) from total energy generated, divided by total energy generated minus powerhouse consumption, multiplied by 100% (McMahon, email, 2019):

$$\left(\frac{\textit{Total Energy Generated-Powerhouse Consumption-Total Energy Sold}}{\textit{Total Energy Generated-Powerhouse Consumption}}\right)*100\% \qquad (5)$$

In Equation (4), *num_total_cust* is used as a measure of customer base because monthly electricity sales data is available in the PCE dataset. Hamilton et al. (2012) note that community population appears to work as well or better than the utility's count of customers in predicting electricity use, but community-level population data is not available on a monthly basis. Different customer types consume vastly different quantities of electricity: Table 4 reports average electricity consumption in kWh for each customer type listed in the dataset. Customer types that are PCE-eligible include residential (subsidized up to 500 kWh per month) and community facilities (subsidized up to 70 kWh per month multiplied by the number of community residents), while state and federal government (including schools) and commercial customers are not eligible for the program (AEA, 2019c). As expected, commercial customers consume the largest amount of electricity on average, at 3,061 kilowatt-hours per month. This category includes energy intensive industries such as fish processing and large electricity users like hospitals and grocery stores. Worth noting is the average residential consumption of 437 kilowatt-hours per month. This is just below the monthly PCE subsidy cap, suggesting that residential customers adjust their consumption behavior to stay within the maximum subsidy limit as noted by Meléndez (2012).

Table 4. *Average electricity consumption per customer type.*

Average Electricity Consumption (kWh/month)	
Residential	437
Commercial	3,061
Community	2,366
Government	2,242

During data cleaning, three wind communities – Kokhanok, Wales, and Pilot Point – were excluded from the dataset because they had poor and inconsistent wind energy generation data. These three communities had challenges integrating their wind turbines and do not accurately represent a properly functioning renewable energy project (Vaught, personal interview, 2019). For simplicity, several other wind communities were excluded because they are connected by a transmission intertie with each other or with non-wind communities. Intertied communities pose a challenge regarding data distinction because either one community shares power across multiple customer bases or they jointly produce power that's shared between them. In the PCE dataset, it is not clear for intertied communities which data is individual and which is grouped, which utility produced power and when, and the direction of power flow between communities. As a result, some successful wind projects were excluded from the sample to not distract from the analysis.

Visual inspection of key variables revealed obvious outliers in some cases and adjustments were made as needed to specific data points. Some of these outliers seemed to have been due to human coding error, where an extra zero was accidentally added to the end of a number for example. A trend was also seen with several communities where they all had a missing value for their diesel generation data for the same point in time, August 2016. The systematic nature of this missing value suggested a centralized data coding error. This was corrected by replacing the missing values with the average of the values of the surrounding months' data – July and September 2016. A similar systematic error was noticed in the values of *num_total_cust* during the same months of late 2016 and early 2017, where many communities' data dipped or spiked dramatically. This was corrected by replacing the erroneous values with the averages of the values for surrounding months.

The *line_loss* variable was calculated using data points for total generation, powerhouse consumption, and electricity sold to each customer type as AEA does not report line loss in the PCE dataset. The calculated line loss variable contained several negative values which shouldn't occur given that a utility cannot sell more power than it produced. Plots of the line loss data for each community revealed relatively stable series that are highly variable month to month but fluctuate around a consistent average value (around 7%). Consultation with the Alaska Energy Authority (McMahon, email, 2019) confirmed that the negative values are likely mistakes in the input data, e.g., mis-read meters, bad meters, or incorrect data entry. The negative values were corrected by replacing them with the mean of the adjacent observations or replacing them with the mean of the series in cases of consecutive negative values.

Table 5 reports descriptive statistics for the data. Statistics are presented for the variables included in final estimation (indicated by italics) as well as for input variables.

Table 5. Descriptive statistics of data, July 2001-June 2017.

Variable	Units	Mean	Standard Deviation	Minimum	Maximum
Diesel Fuel Used (*gen_fuel*)	Gallons	32,118.7	46,989.1	3,652	276,216
Wind Penetration (*wind_pen*)	Percentage	15.9	11.8	3.52×10^{-4}	69.9
Wind Penetration^2 (*wind_pen*^{2})		392.9	502.2	1.24×10^{-7}	4,886.5
Wind Energy Generated	kWh	62,666.1	79,642.6	1	682,096
Total Energy Generated	kWh	501,558.8	766,476.3	44,143	4,198,299
Total Customers (*num_total_cust*)		437.0	521.9	80	2,191
Residential Customers		344.8	424.8	29	1,761
Commercial Customers		53.8	73.3	0	367
Community Customers		19.4	17.7	0	255
Government Customers		17.5	18.4	0	66
Unbilled Customers		0.3	0.8	0	9
Line Loss (*line_loss*)	Percentage	6.9	5.9	0.01	55.5
Residential Electricity Sold	kWh	161,109.6	221,474	0	1,108,331
Commercial Electricity Sold	kWh	196,428.3	349,837.2	1,455	3,044,995
Community Electricity Sold	kWh	54,369.2	69,599.8	1,979	390,710
Government Electricity Sold	kWh	49,702.6	90,693.8	0	888,222
Unbilled Electricity	kWh	205.3	5,482.5	0	279,378
Powerhouse Electricity Used	kWh	14,058.6	29,415.5	0	468,505

Note: Statistics reported for wind penetration and wind energy generated exclude months with no wind generation.

Table 6 reports diesel fuel consumption in gallons for each community before and after wind project completion. Of primary interest is the change in mean and maximum consumption following wind integration. As anticipated, most communities' fuel consumption decreases following the adoption of renewable energy. Interestingly, a few communities, such as Emmonak[12], show increases which are likely due to other factors affecting consumption.

[12] Emmonak was connected with the nearby village of Alakanuk by transmission intertie and has been providing electricity to both communities since August 2016 (Stamm, email, 2019), so their fuel consumption increased significantly as a result of the increase in customer base.

Table 6. *Diesel fuel consumption before and after wind integration.*

		Monthly Diesel Fuel (*gen_fuel*) Consumption, in gallons			
		N (months)	Mean	Min	Max
Buckland	Before	170	10,040	4,066	23,319
	After	22	9,198	4,713	18,767
Chevak	Before	104	15,076	9,387	20,495
	After	88	11,954	6,290	18,748
Emmonak	Before	123	17,632	12,433	29,528
	After	69	21,292	4,249	34,771
Gambell	Before	103	11,747	7,522	15,973
	After	89	9,568	4,708	14,601
Hooper Bay	Before	95	16,300	11,053	23,768
	After	97	16,977	11,719	26,318
Kotzebue	Before	38	122,976	102,356	154,006
	After	154	114,348	78,123	172,298
Mekoryuk	Before	114	5,448	4,042	7,573
	After	78	4,992	3,652	6,885
Nome	Before	104	165,977	124,374	276,216
	After	88	169,823	141,404	243,479
Quinhagak	Before	113	10,914	7,893	22,409
	After	79	10,405	6,556	33,510
Sand Point	Before	130	24,684	16,683	31,728
	After	62	19,391	14,753	30,226
Savoonga	Before	96	12,568	9,298	15,987
	After	96	11,621	8,027	25,077
Selawik	Before	57	17,781	9,761	27,796
	After	135	16,999	9,062	30,401
Shaktoolik	Before	129	5,225	3,889	10,357
	After	63	5,046	4,168	7,627
Unalakleet	Before	102	24,796	18,377	29,456
	After	90	19,935	14,072	25,660

Because of anticipated differences in the effect of wind energy generation on fuel use at various penetration rates and electrical loads, Equation (4) is estimated for the full sample and separately for sub-samples of low and high average wind penetration panels and small and large customer base panels. Specifically, 7 communities are classified as relatively low average penetration (<17%): Selawik, Nome, Buckland, Kotzebue, Emmonak, Savoonga, and Hooper Bay, and 7 are classified as relatively high average penetration (>17%): Mekoryuk, Sand Point, Unalakleet, Gambell, Quinhagak, Shaktoolik, and Chevak. The division point was made based on distribution of data presented in Table 3. The parameter estimated for *wind_pen* is expected to be larger in the high penetration sub-sample because a larger proportion of total electricity is generated by wind (offsetting more diesel fuel) than in low penetration systems.

Similarly, the communities were also categorized into the following customer base groupings: small customer base (<250 customers) – Shaktoolik, Buckland, Mekoryuk, Savoonga, Quinhagak, Gambell, Chevak, and Selawik; and large customer base (>250 customers) – Emmonak, Hooper Bay, Unalakleet, Sand Point, Kotzebue, and Nome. Customer base is correlated with community population but will always be smaller than population – residential customers are households, and each household may have several individual members. The community with the smallest average customer base is Shaktoolik, with 91 customers, and the largest is Nome, with 2,057 customers. The coefficient on the customer base variable *num_total_cust* is anticipated to be smaller in the large customer base sub-sample than the small customer base sub-sample because communities with many customers can capture economies of scale in their electricity generation and distribution system, so each additional customer is expected to require less additional generator fuel.

Empirical Results

Three modeling issues must be addressed before presenting empirical results. First, serial correlation tests are utilized to test for covariance between errors. This is not necessary for the pooled mean group (PMG) or mean group (MG) estimators but is needed for the dynamic fixed effects (DFE) estimator. A method outlined by Wooldridge (2002) is used to test the null hypothesis that there is no serial correlation in the panel data. With an F-statistic of 21.54, the null hypothesis is strongly rejected, indicating the presence of serial correlation in the errors.

The second issue to be addressed is the presence of unit roots in the panel data. A unit root, or non-stationarity, means that a variable's value in this time period is linked to its value in the last time period. The PMG, MG, and DFE estimators can be applied in the case that variables are a mix of stationary, I(0), and non-stationary integrated of order one, I(1), but they cannot be applied in the case that variables are I(2) or higher. Four different unit root tests are implemented to test whether any of the variables are I(2): the Im-Pesaran-Shin (IPS), Fisher- Augmented Dickey Fuller (ADF), Fisher- Phillips-Perron (PP), and Hadri LM tests. IPS, Fisher ADF, and Fisher PP test the null hypothesis that all panels contain unit roots against the alternative that at least one panel is stationary. These three tests were chosen because they allow the autoregressive parameter to be panel-specific, a feature that fits best with the differences in population, electrical infrastructure, and wind resource between the rural community panels in the dataset. Additionally, these three tests use sequential limit theory to determine that the test statistic will have a well-defined asymptotic distribution, meaning that first the time dimension T goes to infinity, followed by the number of panels, N. These tests work best with "large" T and "moderate" N, which is the case with this dataset.

The results of the IPS, ADF, and PP tests indicate that all variables in the full samples and sub-samples are either I(1) or I(0) processes. The Hadri LM test was also conducted to look at the stationarity of the variables from a different perspective: it tests the null hypothesis that all panels are stationary against the alternative that some panels contain unit roots. The results from this test confirmed that all variables are at most I(1), which can be corrected with the first difference approach of the ARDL model. No variable in the dataset is I(2), so the PMG, MG, and DFE estimators can be applied. Unit root test results for the full sample are presented in Table 7[13].

Table 7. *Results of panel unit root tests*

	IPS		Fisher ADF		Fisher PP		Hadri LM	
Variable	Level	First Difference	Level	First Difference	Level	First Difference	Level	First Difference
gen_fuel	-17.09	-	-16.81	-	-19.69	-	63.89	-3.81
	[0.00] ***		[0.00] ***		[0.00] ***		[0.00] ***	[0.99]
wind_pen	-7.78	-	-8.07	-	-11.26	-	284.94	-3.92
	[0.00] ***		[0.00] ***		[0.00] ***		[0.00] ***	[1.00]
wind_pen^2	-14.25	-	-14.32	-	-19.59	-	198.97	-4.02
	[0.00] ***		[0.00] ***		[0.00] ***		[0.00] ***	[1.00]
num_total_cust	-2.48	-	-2.59	-	-3.61	-	390.19	-3.21
	[0.01] ***		[0.00] ***		[0.00] ***		[0.00] ***	[0.99]
line_loss	-21.35	-	-20.27	-	-26.47	-	90.14	-4.01
	[0.00] ***		[0.00] ***		[0.00] ***		[0.00] ***	[1.00]

Notes: For the IPS, ADF, and PP tests, ** and * denote rejection of the null hypothesis that all panels contain a unit root at the 5% and 10% significance levels, respectively. For the Hadri LM test, ** and * denote rejection of the null hypothesis that all panels are stationary at the 5% and 10% significance levels, respectively. *p*-values are in brackets. All tests include a constant.

A third modeling issue to be addressed prior to model estimation is to test whether the data exhibits cointegration, the existence of a long-run relationship between two or more variables. This is done by applying panel cointegration tests outlined by Pedroni (1999); results are presented in Table 8. A key feature of cointegrated variables is their return to a long-run equilibrium following a deviation. In all cases, the no-cointegration null hypothesis is strongly rejected, indicating a long-run relationship. The estimated value of the error correction term, EC, – Φ_i in Equation (4) – is another means of revealing cointegration in the full sample and each sub-sample. Specifically, a value of EC between zero and negative one indicates cointegration.

[13] Similar results are obtained from the sub-samples, so only the results from the full sample are reported for brevity.

Table 8. *Results of panel cointegration tests*

Variable	Full Sample	Low (<16%) Avg Penetration Sub-sample	High (>16%) Avg Penetration Sub-sample	Small Customer Base (<250)	Large Customer Base (>250)
Modified PP Statistic	-31.444 ***	-23.048 ***	-20.000 ***	-24.506 ***	-19.735 ***
PP Statistic	-23.710 ***	-17.029 ***	-15.897 ***	-18.480 ***	-14.880 ***
ADF Statistic	-22.722 ***	-16.181 ***	-15.953 ***	-17.656 ***	-14.321 ***

Notes: *** denotes rejection of the null hypothesis of no cointegration at the 1% significance level. All tests include a lag of 1.

Results for the Full Sample

Table 9. *Results of alternative estimates of the full sample.*

Variable				Includes *winter* variable in short-run		
	(1) Pooled Mean Group (PMG)	**(2) Mean Group (MG)**	**(3) Dynamic Fixed Effects (DFE)**	**(4) Pooled Mean Group (PMG)**	**(5) Mean Group (MG)**	**(6) Dynamic Fixed Effects (DFE)**
EC	-0.357	-0.446	-0.363	-0.456	-0.591	-0.395
	(0.041) ***	(0.041) ***	(0.015) ***	(0.042) ***	(0.041) ***	(0.015) ***
wind_pen	-68.019	-1,076.416	-284.61	-43.242	-868.436	-233.053
	(17.114) ***	(770.129)	(101.40) ***	(11.522) ***	(658.723)	(91.260) **
wind_pen^2	1.116	71.110	5.281	0.232	35.492	2.570
	(0.461) **	(56.723)	(3.055) *	(0.329)	(32.349)	(2.755)
num_total_cust	42.397	56.173	40.545	36.468	57.952	40.328
	(7.586) ***	(32.971) *	(12.582) ***	(5.006) ***	(24.001) **	(11.311) ***
line_loss	27.222	525.794	211.574	14.283	308.141	156.568
	(17.172)	(435.651)	(73.801) ***	(12.394)	(253.043)	(66.386) **
Constant	4,882.3	3,292.7	5,129.9	5,746.5	-3,167.7	4,386.9
	(2,535.2) *	(24,158.8)	(2,024.1) **	(2,946.9) *	(21,589.3)	(1,980.2) **
Observations	2,674	2,674	2,674	2,674	2,674	2,674

Notes: Standard errors are in parentheses. ***, **, and * indicate the 1%, 5%, and 10% significance levels, respectively.

Table 9 reports estimation results for the full sample where Equation (4) is estimated by three alternative models in columns (1-3). The Hausman test was attempted but the fitted model failed to meet asymptotic assumptions required for the test. The PMG model is chosen as the best fit in lieu of Hausman test results because it is the only model of the three that imposes a homogeneity constraint on the long-run parameters (Blackburne III & Frank, 2007). The PMG estimator is less prone to influence from data outliers than the MG or DFE estimators, an important feature given the significant range of monthly diesel fuel consumption between community panels demonstrated in Table 6. The presence of large communities such as Kotzebue and Nome in the dataset likely skews the MG estimation results to be too high, as evidenced by the coefficient on *wind_pen* in column (2) of Table 9. The estimated long-run offset of 1,076 gallons (statistically insignificant even at the 10% level) of diesel fuel per 1% increase in wind utilization does not make sense for many of the communities in the sample given their average monthly fuel consumption of only five to ten times this amount. Conversely, the DFE estimator (results reported in column (3) of Table 9) does not tell the whole story as it only estimates the within-panel variance while ignoring between-panel variance. It also restricts the speed of adjustment coefficient and short-run coefficients to be equal (Blackburne III & Frank, 2007) – too limiting of a constraint given significant data variability among panels.

Because the PMG estimator is chosen as the best model, a correction for serial correlation is not needed. The long-run results of the PMG method (column (1) of Table 9) indicate that *wind_pen* is negatively related to *gen_fuel* and the quadratic term $wind\_pen^2$ is positively related, demonstrating that increases in wind penetration offsets fuel consumption at a decreasing rate, exhibiting parabolic form. After a turning point, further increases in wind penetration have a negative effect on fuel consumption in the powerhouse. Specifically, the coefficient on *wind_pen* is -68.019 (highly significant[14]) and on $wind\_pen^2$ is 1.116 (significant at the 5% level), indicating that before (after) a penetration threshold, a 1% increase in wind penetration leads to a decrease (increase) in fuel consumption by about 68 (1.12) gallons. The turning point is calculated at 30.47,

[14] Coefficients that are statistically significant at the 1% level are termed "highly significant".

which suggests that beyond average monthly wind penetration levels of about 30%, additional wind utilization increases are associated with greater fuel usage. This finding is consistent with expert opinions on wind-diesel systems – average penetration levels beyond about 30%, without additional control mechanisms or battery storage, are difficult to manage and require wind turbine output to be curtailed to ensure system stability (V3 Energy, 2018). Wind-diesel systems that are not optimized for higher penetration output levels cannot realize additional fuel savings beyond this point.

The estimated coefficient on *num_total_cust* is positive and highly significant, indicating that diesel fuel consumption increases with population-driven increases in demand. This finding is consistent with demand theory that increases (decreases) in customer base are associated with increases (decreases) in production inputs needed – in this case, diesel fuel – to accommodate the resulting increase (decrease) in total energy demand. In particular, each additional customer is estimated to require about 42 gallons of diesel fuel, on average.

Finally, the coefficient on *line_loss* has the expected sign although it is not statistically significant. The results suggest that each 1% increase in line loss rate, an indication of increasing transmission and distribution inefficiencies, is associated with an increase in fuel usage of about 27 gallons to make up for that loss of electricity that does not make it to consumers.

The coefficient on the error correction term (EC) is negative and highly significant, confirming cointegration[15]. EC tells the speed of adjustment back to equilibrium following a shock. The estimated error correction parameter for the full dataset is -0.357, meaning that it takes slightly

[15] If the coefficient on the EC term, Φ_i, equals zero and is statistically significant, or is statistically insignificant, then there would be no evidence of cointegration. However, a significantly negative EC parameter with a value between 0 and -1 indicates that the variables show a return to a long-run equilibrium following a deviation, a principal feature of cointegrated variables (Blackburne III & Frank, 2007).

less than 3 months for fuel consumption to return to its long-run equilibrium after a significant change in one of its determinants. Interpreted in terms of the elasticity of fuel consumption to increases or decreases in wind utilization level, the absolute value of the error correction value estimated is less than 1, indicating an inelastic relationship between the two variables. This is unsurprising – given that the communities analyzed are unable to achieve high-penetration diesels-off operation, their diesel generators remain running no matter how much wind-generated electricity is added to the grid. Fuel consumption is relatively insensitive to changes in wind penetration rates – increases in wind utilization will have a limited effect on fuel consumption as the low penetration systems won't allow for generators to be turned off completely, only to be turned down or for generation to be shifted from larger to smaller units.

A variation of Equation (4) that includes an indicator variable for winter months is also estimated by the three alternative methods and reported in columns (4-6) of Table 9. *Winter* is a binary variable equal to 1 for the months October through March, and 0 for the months April through September. Given the extreme seasonality in community fuel consumption data exhibited in Figure 2, a control for winter months is included on the short-run side of the model equation to estimate a fixed parameter effect on generator fuel use for winter months versus summer months. Higher rates of fuel use are expected in winter months when school is in session and Arctic and sub-Arctic communities experience a significant decline in daylight (leading to increased use of indoor and outdoor lighting) and drop in temperatures (leading to increased use of electricity to power heater fans and car plug-ins). *Winter* is included only on the short-run side of the equation; the PMG model did not converge with *winter* included in the long-run, and a long-run trend in fuel consumption in winter months is not expected in the data.

Column (4) reports the PMG results of the *winter* model variation. The coefficient on *wind_pen* is -43.242 and highly significant, but the coefficient on $wind\_pen^2$ (0.232) is not statistically significant, limiting interpretability of the quadratic variable. The coefficient on *num_total_cust* (36.468) is highly significant and consistent with the result found in column (1); the coefficient on *line_loss* (14.283) is not statistically significant. The short-run coefficient on the *winter* variable is not reported in Table 9 because was not included on the long-run side of Equation (4). It is estimated at 2,957.91 and is highly significant, indicating that monthly powerhouse diesel fuel consumption is nearly 3,000 gallons higher on average during the winter compared to the summer. This is a reasonable result given that across the dataset average monthly consumption rates range from 29,700 gallons during summer months to 34,400 gallons during winter months; a roughly 9% difference in fuel use between seasons is realistic. The estimated EC term is -0.456 and highly significant, indicating a shorter adjustment time back to equilibrium following a shock than was estimated for Equation (4) without *winter* included.

Results for Penetration Rate Sub-Samples

Table 10. *Results of alternative estimates of the low and high penetration sub-samples.*

Variable	Low (<16%) Average Wind Penetration Sub-Sample			High (>16%) Average Wind Penetration Sub-Sample		
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
	PMG	**MG**	**DFE**	**PMG**	**MG**	**DFE**
EC	-0.364	-0.439	-0.365	-0.351	-0.453	-0.395
	(0.070) ***	(0.079) ***	(0.021) ***	(0.050) ***	(0.035) ***	(0.022) ***
wind_pen	-120.956	-1,943.912	-361.577	-63.465	-208.920	-191.803
	(73.217) *	(1,522.008)	(296.987)	(17.635) ***	(52.292) ***	(32.561) ***
wind_pen^2	2.852	139.457	2.863	1.000	2.764	2.964
	(2.965)	(111.286)	(12.066)	(0.471) **	(0.821) ***	(0.937) ***
num_total_cust	49.627	85.613	53.223	41.780	26.733	26.025
	(15.543) ***	(64.210)	(21.545) **	(8.811) ***	(17.285)	(6.597) ***
line_loss	51.184	984.623	292.790	14.290	66.965	-4.303
	(29.015) *	(866.568)	(118.518) **	(21.061)	(36.283) *	(37.216)
Constant	7,345.3	2,467.5	6,243.4	907.0	4,117.9	3,052.4
	(4,066.3) *	(50,238.5)	(4,925.8)	(193.2) ***	(2,234.7) *	(681.7) ***
Observations	1,337	1,337	1,337	1,337	1,337	1,337

Notes: Standard errors are in parentheses. ***, **, and * indicate the 1%, 5%, and 10% significance levels, respectively.

Table 10 summarizes results for the low and high penetration sub-samples estimated by the three alternative estimators. Discussion focuses on the PMG results following the reasoning utilized in model choice for the full sample. The long-run results of the low average penetration sub-sample (column (1)) show that *wind_pen* is negative and *wind_pen*^{2} is positive, however, only *wind_pen* is statistically significant (at the 10% level). The coefficient on *wind_pen* is -120.956 and the coefficient on *wind_pen*^{2} is 2.852, indicating a potential turning point where low average penetration systems see decreases in fuel offset beyond 21.21% penetration – but the statistical insignificance of *wind_pen*^{2} reduces direct interpretability. The coefficient on *num_total_cust* is positive, highly significant, and consistent with estimates from the full sample. Finally, the coefficient on *line_loss*, which is significant at the 10% level, indicates an increase in fuel consumption by about 51 gallons with each 1% increase in line loss. The EC term is -0.364 and highly significant, similar to that of the full dataset.

The long-run results of the high average penetration sub-sample (column (4) of Table 10) show that *wind_pen* is negative and highly significant and $wind\_pen^2$ is positive and significant at the 5% level. The coefficient on *wind_pen* is -63.465 and the coefficient on $wind\_pen^2$ is 1.000, resulting in a turning point where high penetration systems do not see decreases in their fuel offset until beyond 31.73% average penetration, supporting the hypothesis that these systems are better optimized to handle larger amounts of wind energy. The coefficient on *num_total_cust* is positive and highly significant, and the coefficient on *line_loss* is not statistically significant. The EC term is -0.351 and highly significant, again consistent with that of the full sample.

The turning points on the wind_pen variable for the low penetration sub-sample, the full sample, and the high penetration sub-sample are 21.21%, 30.47%, and 31.73%, respectively. These results match expectations that communities with low average penetration systems are least suited to handle large amounts of wind energy input on the system, likely having simple control systems and being forced to respond to surplus wind production with curtailment, whereas communities with high average penetration systems possess more complex control systems that can handle larger amounts of wind, resulting in a larger offset of diesel fuel. The turning point for the full sample falls between the two.

Results for Customer Base Sub-Samples

Table 11. *Results of alternative estimates of the small and large customer base sub-samples.*

Variable	Small Customer Base (<250) Sub-Sample			Large Customer Base (>250) Sub-Sample		
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
	PMG	**MG**	**DFE**	**PMG**	**MG**	**DFE**
EC	-0.423	-0.473	-0.407	-0.321	-0.409	-0.367
	(0.057) ***	(0.057) ***	(0.021) ***	(0.072) ***	(0.063) ***	(0.023) ***
wind_pen	-57.507	-358.302	-92.348	-343.785	-2,033.901	-480.749
	(17.287) ***	(157.856) **	(38.823) **	(65.255) ***	(1,797.427)	(272.303) *
wind_pen^2	0.891	22.895	0.875	3.488	135.397	6.002
	(0.455) **	(13.563) *	(1.075)	(2.210)	(133.152)	(10.154)
num_total_cust	46.671	61.685	54.399	9.552	48.822	47.273
	(11.970) ***	(22.965) ***	(15.634) ***	(7.456)	(74.776)	(19.337) **
line_loss	28.543	51.052	48.669	107.001	1,158.78	533.180
	(17.554)	(45.273)	(28.314) *	(69.458)	(1,003.663)	(170.329) ***
Constant	911.551	439.3	374.4	20,058.6	7,097.3	8,489.6
	(325.074) ***	(1,401.2)	(1,152.8)	(9,569.7) **	(59,431.1)	(5,578.3)
Observations	1,528	1,528	1,528	1,146	1,146	1,146

Notes: Standard errors are in parentheses. ***, **, and * indicate the 1%, 5%, and 10% significance levels, respectively.

Table 11 summarizes results for the small and large customer base sub-samples. Discussion again focuses on the PMG results. The long-run results of the small customer base sub-sample (column (1)) have the expected negative and positive signs on *wind_pen* and *wind_pen*^{2}, respectively. With a highly significant coefficient on *wind_pen* of -57.507 and a significant (at the 5% level) coefficient on *wind_pen*^{2} of 0.891, increases in wind penetration in communities with relatively small customer bases (<250) increases fuel consumption beyond 32.27% average penetration, consistent with results from the full sample. The coefficient on *num_total_cust* is positive and highly significant; the coefficient on *line_loss* is not statistically significant. The EC term is -0.423 and highly significant, indicating slightly shorter recovery time to long term trends than that of the full dataset.

The long-run results of the large customer base sub-sample reveal a much larger effect of increases in penetration level on fuel consumption than for the other sub-samples or the full sample. The coefficient on *wind_pen* is -343.785 and highly significant and the coefficient on $wind\_pen^2$ is 3.488 but statistically insignificant. Wind-diesel systems in communities with large customer bases (>250) on average appear not to see declines in their fuel offset until beyond 49.28% average penetration, perhaps indicating that these systems are more capable of handling higher proportions of wind energy because they have larger overall grids and more sophisticated systems. However, the insignificant $wind\_pen^2$ term may be preventing direct interpretation. Neither of the coefficients on *num_total_cust* nor *line_loss* is statistically significant. Although insignificant, the coefficient on num_total_cust is 9.55 which is quite a bit smaller than that for the small customer base sub-sample of 46.67, offering potential evidence of economies of scale in larger communities where each additional customer has less of an impact on overall energy demand, and the fuel use needed to meet that demand, than in smaller communities. The EC term is -0.321 and highly significant.

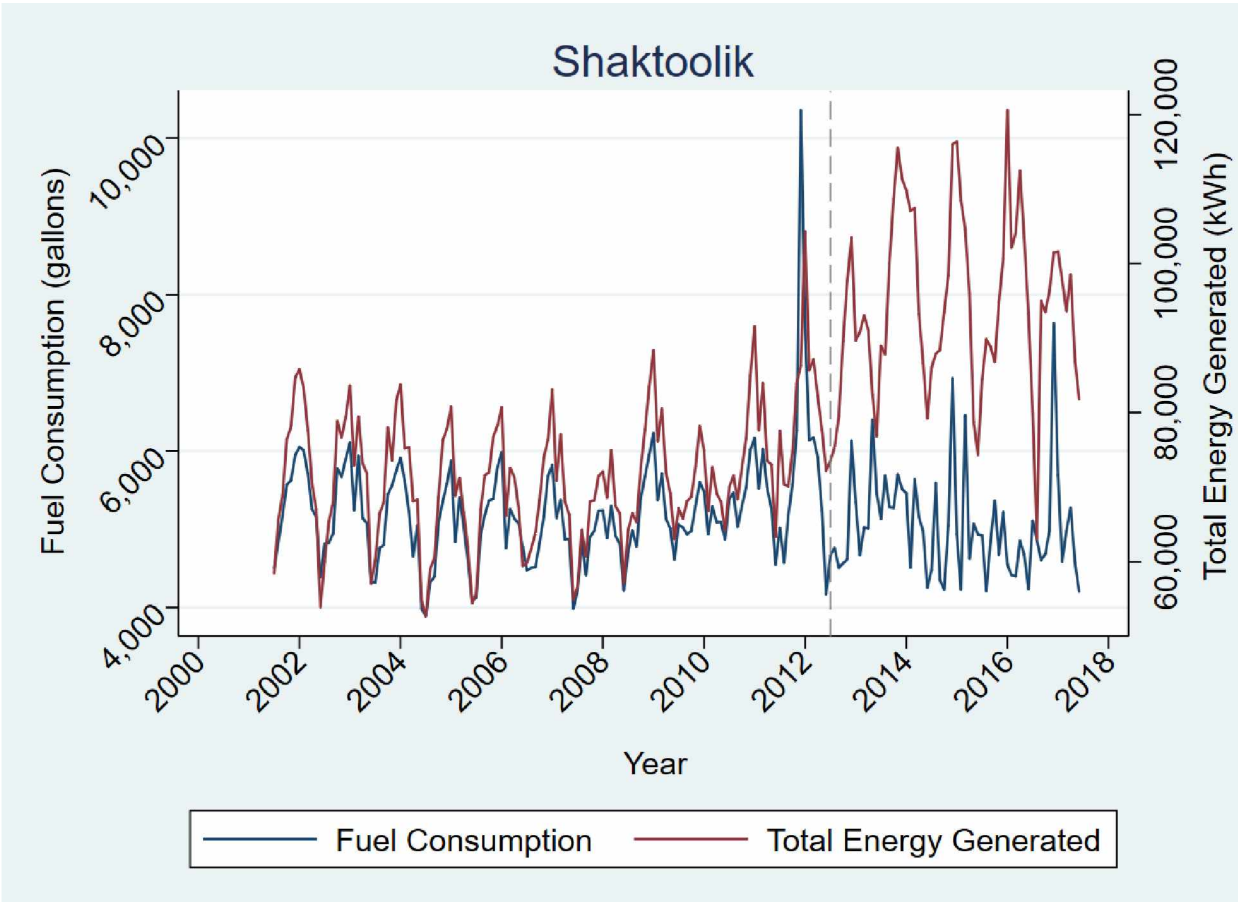
Discussion

Regression results generally show that fuel savings potential from the wind-diesel hybrid systems analyzed drops off beyond 30% average penetration rates, demonstrating that this is an upper limit beyond which additional wind energy input must be curtailed. This finding is consistent across the full sample and sub-samples for both high and low penetration and small customer base communities, providing supporting evidence that wind-diesel hybrid systems that are not diesels-off-capable are limited in the extent to which they can utilize their renewable resource and capture diesel fuel savings.

Figures 3-5 demonstrate three different effects of wind integration on diesel fuel consumption for the communities of Shaktoolik, Selawik, and Mekoryuk, respectively. The vertical dashed line marks the date that the wind system came on-line in each community. The graphs plot fuel consumption on the left-side Y-axis and total energy generation, which is made up of both diesel and wind energy after the integration date, on the ride-side Y-axis. As expected, a very close relationship between fuel consumption and total energy generation can be seen prior to renewable integration when electricity was solely generated using diesel fuel.

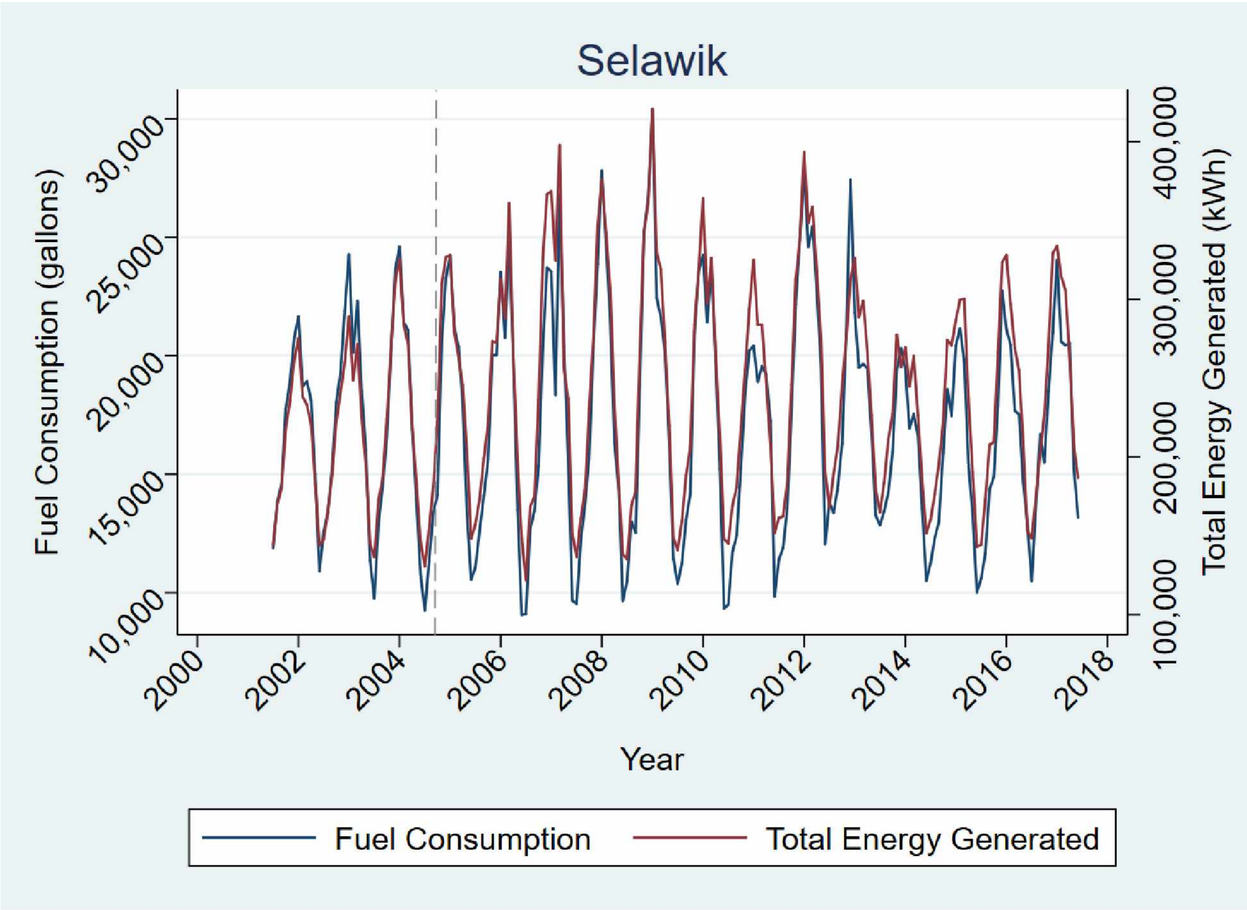
In Shaktoolik (Fig. 3), a decoupling between the variables is seen following wind integration, where total energy generation is higher relative to pre-integration values and fuel consumption is lower. Adding wind allowed Shaktoolik to consume more energy with less fuel. While Shaktoolik did experience a roughly 10% increase in customer base after 2012, the increase in total energy generation is not due simply to an increase in electricity demand – the utility also installed secondary heat loads in the school as a stabilizing element for their wind-diesel system (Tressel, 2015). Wind-generated electricity in excess of grid demand is dispatched to these electric heaters to be used for space heating instead of necessitating turbine curtailment, allowing for greater overall electricity *and* heating benefits. Shaktoolik can realize these substantial savings because of its relatively high average wind penetration rate of 28.15%.

Figure 3. *Plot of generator fuel consumption against total energy generation for Shaktoolik.*



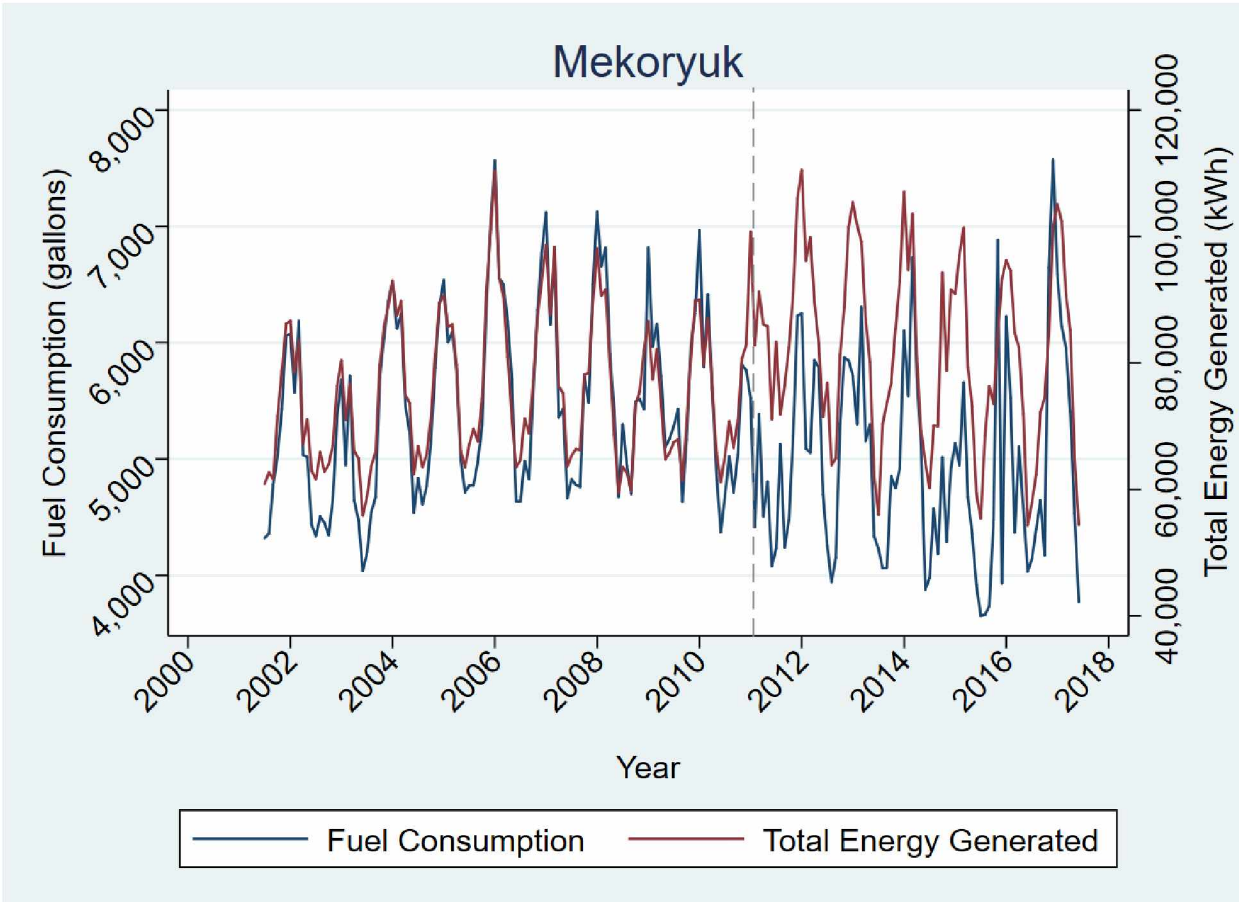
Selawik, on the other hand, does not display any noticeable difference in fuel consumption or decoupling between consumption and total energy generation after wind integration (Fig. 4). The two variables move in sync seasonally before and after integration. The integration of wind energy on the grid does not seem to have any significant effect on decreasing diesel usage to meet overall electricity demand. With a very low average wind penetration rate of only 3.85%, grid input of the renewable is not enough to have a notable effect on system operations, so the diesel generators remain operating at a consistent speed, consuming fuel as usual. Given their minimal wind utilization, fuel consumption in Selawik is very insensitive to the addition of wind energy, which Fig. 4 demonstrates.

Figure 4. *Plot of generator fuel consumption against total energy generation for Selawik.*



A graph for Mekoryuk (Fig. 5) represents a typical case – total energy generation remains about the same while fuel consumption decreases. Mekoryuk has a low to medium average wind penetration of 19.23%, so it can realize more diesel fuel savings than Selawik, for example, but is still limited in resource utilization by its control system configuration. In 2014, Mekoryuk did integrate a secondary heat load system and an electric boiler in their water treatment plant and washeteria, allowing the community to further displace diesel fuel for both electricity generation and space heating (Stamm, email, 2019).

Figure 5. *Plot of generator fuel consumption against total energy generation for Mekoryuk.*



None of the communities in the analysis have energy storage capabilities, and thus are limited in the percentage of total energy generation that can be from wind. There are several different roles that energy storage can play in remote microgrids. Energy storage can provide the capability to bridge lulls in renewable power output, it can ensure power quality by smoothing out fluctuations in renewable generation, and it can store wind-generated energy during periods of low demand and then dispatch it during periods of higher demand (IEA-RETD, 2012). Flywheels[16] can provide very short-term energy storage (seconds or minutes), while batteries can provide storage for hours or days' worth of energy. Lithium-ion-based battery technology is rapidly developing

[16] A flywheel is an energy storage device that stores electrical energy in the form of rotational kinetic energy (Amiryar and Pullen, 2017).

worldwide and being improved for microgrid systems as the lessons learned from early adopters of small-scale renewable energy, including the communities studied, are incorporated into engineering research. While costs for batteries and sophisticated control strategies are declining with advancements in technology, they remain high. Utilities must justify energy storage costs with their associated savings, and an active area of research is in quantifying cost savings in terms of reduced fuel consumption and stress on diesel generators by smoothing out their loading (VanderMeer et al., 2017).

The current paradigm in most rural Alaska microgrids is that the diesel generators not only provide power but also *form* the electrical grid by tightly controlling the frequency[17] and voltage (the power quality). Instantaneous changes in load demand from customers are typically minimal and can be handled by the generators' throttle control system. Power produced by wind turbines, however, represents a *negative* load to a diesel generator: gusts and lulls in the wind inject and remove large amounts of power and the diesel generators, in their grid-forming role, must chase this[18] in order to maintain balance between power supply and demand, especially at higher penetration rates (Vaught, personal interview, 2019).

To achieve maximum fuel savings and achieve diesels-off capability, a utility's goal should be to divorce the diesel generators from frequency control. In a high penetration renewable-diesel-battery hybrid system, a grid-forming invertor takes the place of the diesel generators for this function (Isherwood et al., 2000). Much of the energy demand potentially can be supplied by wind, battery storage can bridge gaps between power supply and demand, and the invertor itself is

[17] Frequency is the number of cycles per second in an alternating current (AC) sine wave, the rate at which electrical current changes direction per second. It is measured in hertz, where 1 hertz is equal to 1 cycle per second. Electrical equipment in North America operates at 60 hertz. Significant deviations in frequency can result in power outages.
[18] Newer, electronically-fuel-injected generators are quicker to respond to changes in demand than older generators, including many in rural Alaska, with mechanical fuel injection technology (Vaught, personal interview, 2019).

responsible for power quality (frequency and voltage). Battery charge is maintained via wind power production in excess of load demand or via diesel generation during times of low wind availability. The diesel generators move into an auxiliary role, only turning on to ensure the batteries remain charged or to meet demand if wind availability is low and the batteries are at a low state of charge. This minimizes diesel O&M costs and maximizes fuel efficiency, as it ensures that diesel engines are only operated as needed and at optimal speed. It also lengthens maintenance cycle time because it significantly reduces the number of run-time hours per year.

Conclusion

This analysis estimates trend-stationary long-run parameters for renewable energy utilization, customer base, and system efficiency, accounting for unit root and cointegration. An autoregressive distributed lag (ARDL) difference-stationary approach is applied to address extreme seasonality of the data. The pooled mean group (PMG) estimator is chosen as the best method to estimate the ARDL model for the mixed integration – I(0) and I(1) – time series. An error correction term is estimated to address long-term cointegration of the data. Regression results capture key long-run relationships between powerhouse diesel fuel consumption and its determinants: wind penetration, customer base, and system efficiency.

Results from the full sample indicate that the fuel offset effect from increases in wind energy utilization drops off beyond 30% average penetration, consistent with wind energy expert opinion that renewable penetration beyond this amount become more difficult to manage (V3 Energy, 2018). Each percentage point increase in wind penetration is associated with a decrease in long-run fuel consumption of 68.02 gallons at average penetration levels below a turning point of 30.47%, after which each additional percentage point increase in wind penetration is associated with a 1.12-gallon increase in fuel consumption, reflecting a non-linear parabolic relationship between the variables. Results from a sub-sample of low wind penetration systems indicate a lower estimated turning point of 21.21%, and results for high wind penetration systems indicate a higher estimated turning point of 31.73%. Estimation results remain consistent for small and large customer base sub-samples as well.

This analysis is limited in its scope and does not consider all of the engineering complexities present in wind-diesel hybrid systems. A panel approach is used to control for unobserved community-specific heterogeneity, allowing for efficient estimation of long-run parameters but omitting characteristics that may be key to wind-energy-induced fuel savings in particular communities. Data availability limitations prevented the inclusion of household-level information such as energy efficiency and conservation efforts or behavioral changes. The model also does not consider changes in the overall make-up of the customer base. Commercial customers use vastly more electricity than residential customers on a per-customer basis, and the loss or gain of large commercial customers can significantly impact overall load.

This analysis treats all wind projects the same other than the average penetration levels. This simplification does not consider essential infrastructure differences in wind turbine models, age, size, quantity, and integration specifications. Wind project distinctions that affect fuel offset include new versus remanufactured turbines[19] and variable pitch versus fixed pitch turbines[20]. Differences in the underlying wind resource were also not considered, including consistency, turbulence, and seasonality of the resource and corresponding availability for energy production. The communities analyzed are in different regions of the state with varying topographical features

[19] New turbines have warranties that cover service disruptions whereas remanufactured turbines have older designs and could be more prone to failure.
[20] Variable pitch is a more complex turbine design and optimizes the angle of the blades based on current wind speed which captures more of the resource. This feature is typically only found on large turbines given the expense. Fixed pitch turbines are smaller and tend to be simpler and less efficient, relying on wind speed assumptions.

and they likely experience differences in their wind regimes. This study excluded intertied wind-diesel communities, such as Toksook Bay-Tununak-Nightmute and Kasigluk-Nunapitchuk, due to data limitations but including this data in future research would provide valuable insight from these successful projects.

This analysis is unable to control for changes in diesel generation efficiency because a determinant of diesel efficiency is diesel fuel, the dependent variable. Including the diesel efficiency variable would have created perfect collinearity in the model. While line loss provides a measure of transmission and distribution system efficiency, a measure of the efficiency of the diesel generators themselves would provide powerful insight into the state of the underlying energy generation system that the renewables are being integrated into. A generation efficiency variable can capture efficiency gains realized by utilities that overhaul, replace, or supplement their diesel-electric generators during the timeframe surveyed. Diesel generator efficiency can also be considered a loose proxy for organizational and management capacity of a community, critical factors for success of a renewable energy project. Utilities that operate properly-sized generators for their load (requiring a mix of engine sizes to handle load diversity) and that regularly conduct recommended maintenance procedures to ensure optimized machine performance (e.g., oil changes) should exhibit higher diesel efficiency rates. Future research that does not use generator fuel as the dependent variable or is able to use an alternate measure of generator efficiency – such as generator age or condition – could account for this important factor.

This paper provides a unique contribution to the existing literature, presenting the first estimation of long-run average parameters for wind utilization-driven diesel fuel offset using an ARDL approach in a remote Arctic microgrid setting. The findings of this paper underscore the importance of energy storage and sophisticated infrastructure to achieve high-penetration diesels-off capability, fully utilize renewable resources, and maximize fuel savings in remote microgrid communities. Existing wind projects without energy storage may fall short of fuel offset expectations due to renewable generation curtailment to maintain system stability. To this end, microgrid utilities and policymakers can use this analysis as evidence supporting high penetration wind energy development for maximum fuel savings and carbon emissions offset. Researchers can utilize the estimation framework of this analysis to inform future energy studies, potentially adding to these results by taking a community-specific time series approach. Future research that builds upon this study's noted limitations, that includes more recent generation data, and especially that incorporates data on energy storage systems will provide additional precision to the savings findings of this analysis.

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