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A Global Daily Solar Photovoltaic Load Coverage Factor Map for Passenger Electric Vehicles

Michelle Wilber
Alaska Center for Energy and Power
University of Alaska, Fairbanks
Anchorage, USA
mmwilber@alaska.edu

Erin Whitney
Alaska Center for Energy and Power
University of Alaska, Fairbanks
Anchorage, USA
erin.whitney@alaska.edu

Christie Haupert
Alaska Center for Energy and Power
University of Alaska, Fairbanks
Anchorage, USA
clhaupert@alaska.edu

***Abstract*— The electrification of transportation is well under way in many parts of the world. However, rural areas, especially those lacking robust electric grid and other infrastructure, are still investigating what it takes to ensure the switch to electric vehicles (EVs) is broadly beneficial and equitable, as well as technologically feasible. For instance, Africa and the Arctic share a challenge of having limits to electrical grid connectivity and capacity, and islanded microgrids are common in both places. Renewable energy generation, such as solar photovoltaics (PV), could be paired with EV charging to help supply the needed energy. To investigate the ability of solar PV to meet this load in different global locations, a daily Load Coverage Factor (LCF) is calculated for an equal amount of installed solar PV capacity and daily driving distance for different global locations and plotted on a map. Regions with lower local insolation and lower winter temperatures have lower LCFs. Generally the global south, including Africa, seems to have a clear advantage in powering electrified transportation with solar PV generation. Specifically, LCFs above 0.8 are common in Africa and other areas of the global south, indicating that over 80% of the daily energy need of an EV driven 30 kilometers per day could be met by 1 kilowatt of installed solar PV.**

***Keywords*— electric vehicles, solar photovoltaics, load coverage factor**

I. INTRODUCTION

The world is in the midst of a transportation evolution to electrification, in large part due to the falling cost of suitable batteries. In some parts of the world, this transformation is in full swing with electric vehicles (EVs) making up nearly two-third of all new car sales in Norway [1,2]. China is on track to reach 20% EV penetration in 2022 and Germany, with the largest market share in Europe, now has a quarter of their car registrations as plug-in electric [3,4]. In other parts of the world, such as Alaska or Africa, the uptake of EVs is still nascent. There are a variety of factors at play, including lack of supporting infrastructure (e.g., charging equipment, electric power system capacity, maintenance availability, and incentives), perceived and real performance degradation in hot or cold climates, high electricity prices, and lack of access to reliable electricity. Meanwhile, the falling cost of solar photovoltaic (PV) generation is causing unprecedented growth in on- and off-grid solar installations [5].

Transportation emissions are a leading, and in many cases growing, cause of dangerous air pollution and greenhouse gasses, for example greenhouse gas emissions from vehicles are growing at 7% a year in Africa [6]. The transition to EVs has the potential to offset harmful emissions from combustion engines, especially if powered by lower emitting sources [7]. This paper aims to investigate and visualize the ability of solar PV to meet EV loads in different microgrid locations worldwide, by calculating a daily Load Coverage Factor [8] for different global locations using an equal amount of installed solar capacity and daily driving distance inputs. The goal is to understand what it takes to ensure the switch to EVs is broadly beneficial and equitable, as well as technologically feasible.

II. METHODOLOGY

A. Energy Consumption versus Temperature for Electric Vehicles

While driving, the energy use of an EV can be simply estimated as the product of the average energy use per unit distance multiplied by the distance driven. The energy use will depend on a number of factors including driver behaviors and route grade but is found to be highly temperature dependent [9]. This is primarily due to the energy use of the cabin and battery conditioning systems that keep the occupants and motive battery of the vehicle at a comfortable and healthy temperature (which is, perhaps surprisingly, not so different for humans and the battery.)

Data on the relationship of energy use with temperature for passenger EVs exist in the literature [10,11,12,13,14], but data below -30°C are sparse. Large regions at extreme latitudes routinely surpass temperatures below -40°C, so data were crowdsourced from EVs in Alaska and are presented in Fig. 1.

Data of EV energy use per unit distance vs. temperature from the literature come from a variety of methods. Some data are from testing where EVs were driven to depletion on a standard course [10] or are from a controlled lab [11, 12], other data are reported by on-board diagnostic systems, or compiled from odometer readings and charging energy use statistics in less controlled driving conditions [13,14]. Some reported values are

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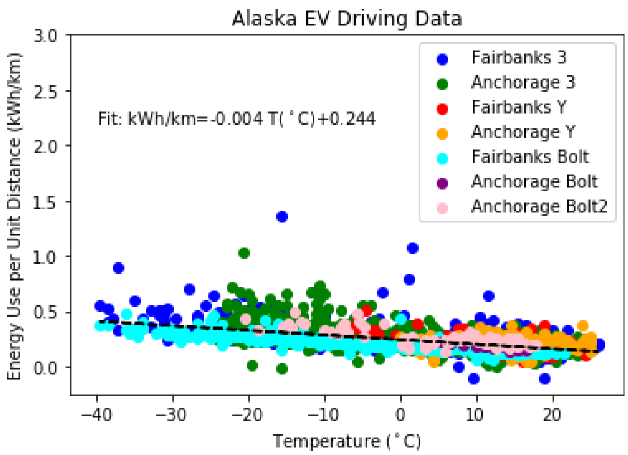

Fig. 1. Crowdsourced trip level data for seven EVs in Alaska, based in either the cities of Fairbanks or Anchorage, with a linear fit to the energy use per unit distance (kWh/km) vs. ambient temperature (°C). Data points are for three models of EVs: dark blue and green data points for Tesla Model 3, red and yellow data points for Tesla Model Y, and light blue, purple and pink data points for Chevy Bolt, respectively.

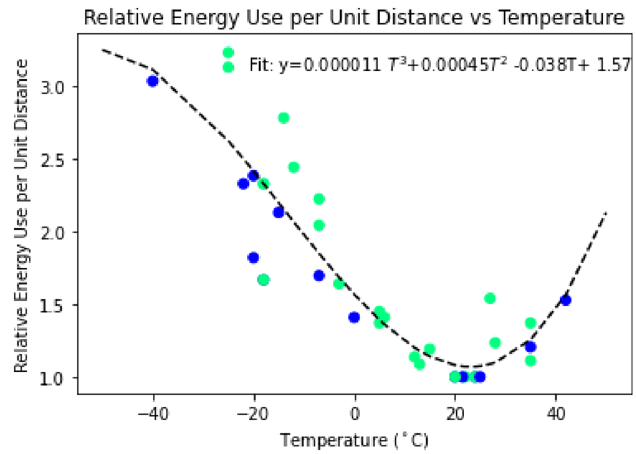

Fig. 2. Effect of temperature on energy use per distance relative to the optimal (lowest) energy use per distance for passenger EVs from the literature [10,11,12,13,14] and from points on the linear fit in Fig. 1. The third order polynomial fit is shown by the dashed line and the equation given. Blue data points are from studies reporting averages and fits to many EVs and trials, and green data points are data from one or two EVs during one or two trials. All points are weighted equally.

given for one or two vehicles with one or two tests at each temperature [10,12,13]. In other cases, average or fit results of many vehicles and/or individual drives are reported [11,14]. For data reported as range loss, an estimate of relative energy use per distance at temperature was calculated:

$$RE(T) = E(T)/E = 1/(1 - RL(T)) \quad (1)$$

Where:

- E(T) is the energy use per unit distance traveled at temperature T
- E is the minimum energy use per unit distance traveled
- RL(T) is the range loss in decimal percent observed at temperature T
- RE(T) is relative energy use per unit distance traveled at temperature T

These data showing relative energy consumed while driving vs. temperature are presented in Fig. 2. Where fit results are given [14, Fig. 1] select points from the curve including the extremes were used. For other sources, the average values or individual test data points are shown. The Python library numpy's polyfit tool was used to fit a third order polynomial to these data, as this was the lowest order that gave a good visual fit. This fit was used to model the relationship between temperature and energy use in subsequent steps.

EVs use energy while parked to keep the battery at a healthy temperature [9]. To determine the effect of temperature on parked energy use, crowdsourced data for two makes of Alaskan EVs are presented in Fig. 3. Tesla data are gathered from the Tezlab App [15]. Chevy Bolt data are gathered from recordings of odometer reading and energy to charge to full (using charger data or plug energy monitoring data). It can be seen that energy use, especially for Teslas, is dependent on factors other than temperature. However a temperature signal is present, and a fit to this data is used to model the energy used by a vehicle while parked. Although unaware of existing data for high temperatures, we believe that energy used to cool the EV battery while parked should lead to increasing energy usage with temperature, to a maximum value, above 25°C. We expect the limits of the battery conditioning system will lead to a maximum value (i.e. always on at maximum power) at some high and low temperature, although the available data do not clearly show that the cold limit has been reached at temperatures above -40°C.

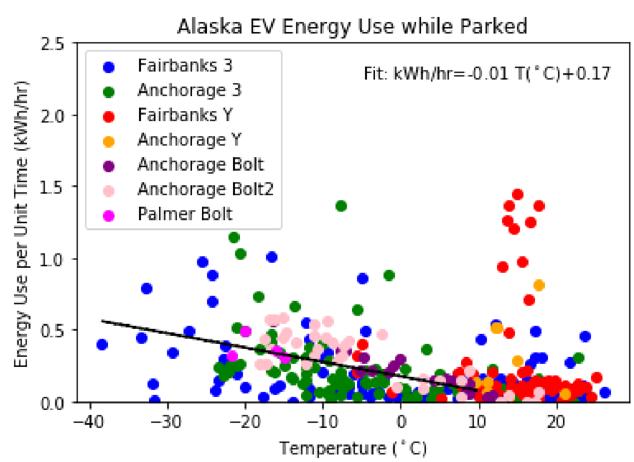

Fig. 3. Crowdsourced parked energy use data (generally at daily or overnight timescales) for seven EVs (two Tesla Model 3s, two Tesla Model Ys, and three Chevy Bolts) in Alaska with a linear fit to the energy use per hour (kWh/hour) vs. ambient temperature (°C). The large amount of variability seen in the Tesla Model 3 (blue and green data points) and Model Y (red and yellow data points) data may be due to quality and completeness issues with the data collection app, introduced analysis errors, or actual variations in energy use from other car features such as cameras that may use energy while the car is parked.

B. Daily Load Coverage Factor

To estimate the ability of solar PV to provide energy for daily EV driving, a daily Load Coverage Factor (LCF) [8] can be computed as:

$$LCF = \frac{\sum_{i=1}^{n} \min\,(L_i, G_i)}{\sum_{i=1}^{n} L_i} \quad (2)$$

Where the subscript *i* refers to the daily values, *n* is the total number of days in the analysis and should be a multiple of 365 (complete years), *Li* are the daily EV energy loads, and *Gi* are the daily solar PV generation totals, and min (*Li*, *Gi*) is the minimum of *Li* or *Gi*.

EV load is calculated as a sum of hourly energy use for a day. This hourly energy use can be calculated as the sum of the driving and parked energy use, which can be calculated as a function of hourly temperature from the relationships in Fig. 2 and Fig. 3, respectively. Hourly weather (including insolation) data and a solar PV system model are used to calculate daily solar PV generation. The LCF can be calculated for any place on the earth with enough weather data to model these values. It can also be calculated for any driving profile desired, which could vary from 3 km per day of driving, such as might occur in rural Alaska for a private vehicle, to hundreds of kilometers of driving per day, such as might occur with a ride-share or commercial vehicle. The size of the solar PV system may be adjusted to optimize the LCF for a given location, within economic constraints.

In practice, we used the online tools PVGIS V.5.2 [16,17] and PVWatts V.6 [18,19] to return hourly temperature data and estimated solar PV generation for a regular grid of latitude and longitude points, capital cities [20], and ground station locations using a default system of 1 kW of ground-mounted, crystal silicon panels oriented toward the equator at a fixed tilt equal to the latitude and assuming 14% system losses. For PVGIS we have used the Python pvlib library's application programming interface (API) tool with the default satellite derived data over a period of years for each location, and for PVWatts we have used the PVWatts API with the Typical Meteorological Year (TMY) datasets for each location in the PVWatts database [21]. Driving habits are individual, and average behaviors vary by location. Alaskan and Kenyan drivers may both, on average, drive about 50 km per day [22,23], but many people drive much less or much more than this. For consistency, we have assumed a driving profile composed of a daily 16 km drive at 48 kph at 8:00 a.m. and again at 5:00 p.m., with the vehicle parked in ambient temperatures the rest of the time. Because of a lack of data on parked energy consumption at high temperatures (which could be higher than ambient temperatures on a paved parking lot), we expect that the model underestimates the parked component of energy use in hot climates. As a spot check on the consistency of PVGIS vs. PVWatts inputs, for Cape Town, South Africa, the calculated LCF was 0.78 for both returned datasets.

III. Results

A map of the resulting LCFs is presented in Fig. 4. A few of the results look anomalous, and further investigation of the returned hourly data files from PVGIS for those data points is needed. However, a comparison to the Global Solar Atlas [24] and an EV Temperature Map [25] show that regions with lower local insolation (due to extreme latitude or maritime climate, for instance) and with lower winter temperatures (due to more polar latitudes, altitude or other factors) do have lower LCFs as expected. The LCFs may be inflated for warmer climates, as data on parked energy use for EVs in hot ambient temperatures is unavailable. Generally the global south, including and perhaps especially, Africa, seems to have a clear advantage in powering

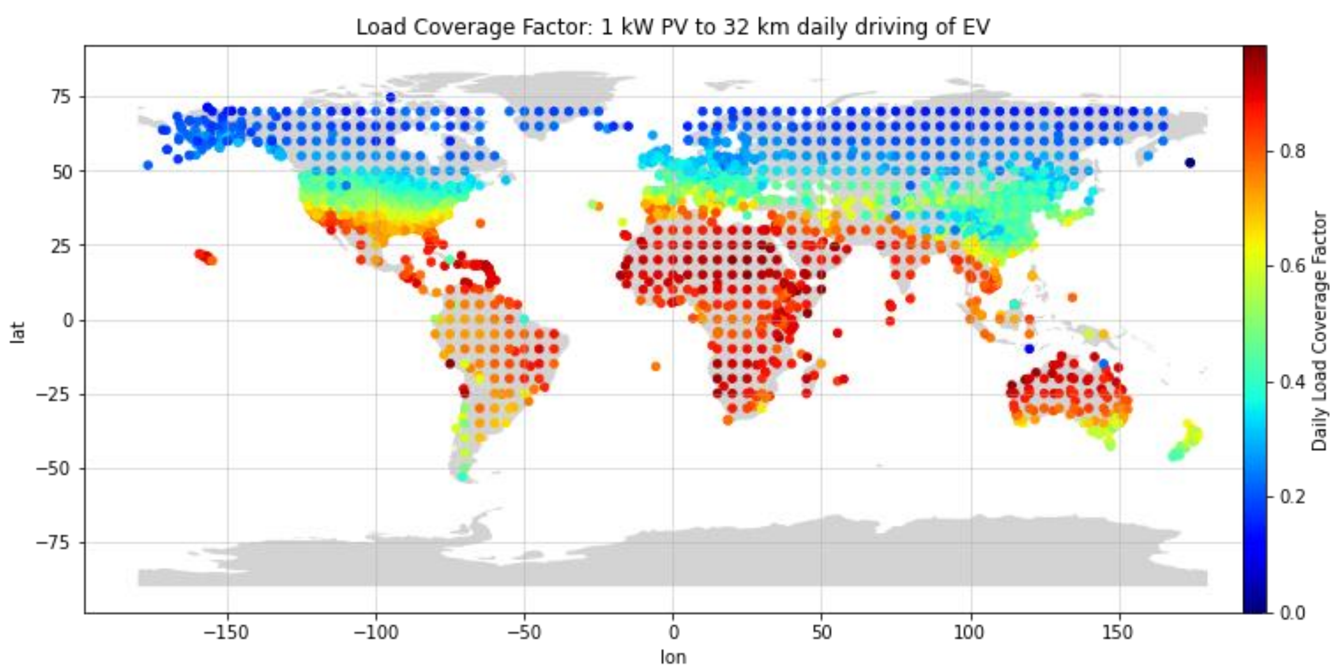

Fig. 4. Daily Load Coverage Factor (LCF) which indicates the percentage of EV energy use for 32 km of daily driving met by 1 kW of installed solar PV production (fixed, at latitude tilt).

electrified transportation with solar PV generation. LCFs above 0.8 are common in Africa and other areas of the global south, indicating that over 80% of the daily energy need of an EV driven 32 km per day could be met by 1 kW of installed solar PV.

IV. Discussion and Further Work

The LCF is calculated at a daily level for convenience, but also because this is a reasonable timescale based on use and production patterns. We make no assumptions about whether or not a solar PV installation is grid connected, or how much other storage may be integrated with it in this calculation. A practical configuration in rural regions with grid infrastructure limitations may be the integration of solar PV directly with EV charging stations as well as small amounts of stationary storage. If charging happened primarily during the day, when the sun is shining (perhaps at workplace or public charging infrastructures), the solar PV generation could be used nearly coincidentally.

Gathering of parked energy use data for EVs in hot climates would allow for a more accurate determination of energy use in these areas. Verification of the actual yearly energy use of EVs against the predictions made with the energy use vs. temperature relationships in this paper would help validate these relationships and their ability to accurately model energy use. We have very limited full year data for EVs in Alaska. While it appears to be in agreement, a larger and more geographically diverse dataset would help to systematically validate this model.

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