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Steven Parker, PE, CEM, Editor-in-Chief
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Editor's Desk

Decarbonization is the New Energy Conservation (and More)

The new buzzword lately is decarbonization. Several organizations have their own definitions, but at its essence the term means to reduce the carbon impact to the atmosphere. There are multiple aspects of this new term. I'll define them here as supply and demand. On the demand side, it means we should use things and methods that use less energy, thereby generating less carbon emissions that get added to the atmosphere. On the supply side, it means generating energy from non-carbon (or at least less carbon-generating) sources. It also means doing things that reduce the already high level of carbon emissions currently in the atmosphere.

When I hear the term "decarbonization," all I hear is a new buzzword for the same old thing we have been doing for over 45 years. Ok, for some people, more than 50 years. From my perspective, there really isn't much new here, just a new buzzword. After the oil embargoes of the 1970s, "energy conservation" was the industry buzzword and started appearing more and more in the press. Yes, there are books and stories covering energy conservation dating back into the 1960s, but it became a headline term in the 1970s. Programs started under the Nixon administration were reorganized and turned into the U.S. Department of Energy under the Carter administration. President Carter had his fireside chats wearing a comfy warm sweater and promoting energy conservation.

Opponents used misinformation tactics to claim energy conservation meant reducing economic prosperity and related fireside chats to freezing in the dark. They showed the correlation between oil consumption and gross domestic product and claimed if we reduce oil consumption, then economic prosperity would surely go down too. It was a lie, but as misinformation goes, it was partially effective. The opponents were wrong. We broke the relationship, proving we could reduce oil consumption while economic prosperity (and GDP) continued to rise.

As an industry, we stopped using the term energy conservation (because it was seen as doing less with less) and coined a new buzzword "energy efficiency" (doing more with less). We also saw the phrase "energy awareness," which I thought of as "stop using energy that didn't need to be consumed" (turn it off when unneeded).

When those terms got old, we created a new buzzword "energy management." As an industrial engineer, I thought of that term as "work smarter, not harder." As time went by, many new technologies became more economically and technically viable. Cogeneration (do more with less) became combined heat and power. Wind, geothermal, solar thermal, and solar photovoltaic were seen as "renewable energy" sources—contrasting with fossil-fuel sources, which were defined as non-renewable, or limited, energy sources. After a while, renewable energy sources were redefined as "green" energy sources contrasting with fossil-fuel systems defined as dirty sources. Eventually, even green was replaced by another buzzword, "sustainable."

As the population of the world increased and nations started consuming more and more, we (eventually?) learned there were consequences to consuming ever increasing amounts of fossil fuels to support our prospering standards of living. Global warming became the new buzzword. Again, counterculture not wanting to limit their growing need for more, used misinformation to confuse weather with climate and deny reality. As a result, we changed buzzwords again, "global warming" became "climate change."

The one thing about science and engineering is that it grows and adapts. Terminology, as a result, also changes, grows, and adapts. When your buzzword grows old or begins to work against you, it's time for a new buzzword. What does all this mean now?

Climate change is happening. You can argue as to whether mankind is the sole cause of it, or only a contributing factor, or not. That argument is irrelevant. Climate change exists, it's happening. It might not impact me much today but it's going to impact the future of mankind. If you're not part of the solution, then you are part of the problem. You might want to decide which role (problem or solution) you are going to play. But I digress.

So, the new buzzword is decarbonization. What does it really mean? Decarbonization is energy conservation. But it also means energy efficiency. It even includes energy management, renewable energy, fuel switching, sustainability, and everything else I've written about. And if we're lucky, it also means removing carbon emissions already in the atmosphere, reducing CO_2 levels below their current levels, not just reducing the current rate of increase. That's an aggressive goal for a new buzzword, but we might get lucky. Our future generations will appreciate our efforts.

As for the misinformation culture out there complaining about the potential cost and how it's going to harm our standard of living (same old scare tactic)—haters' gonna hate. Some people fear change. Scared of the risk. Scared of not having as much as others. They are always out there, have always been out there, will always be out there. Society has never advanced by looking backwards. Society advances by moving forward. I'm not expecting a smooth ride; there will be bumps, but such is the way of progress. In other words, decarbonization means keep doing what we have long been doing.

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Relaxing CV(RMSE) Requirements for Option C M&V Regression Analysis

John Avina, CEM, CEA, CMVP, CxA

ABSTRACT

The Option C Measurement and Verification (M&V) methods for energy service companies (ESCOs) often involve performing regression analysis of utility bills against weather data. We have been advised by the International Performance Measurement and Verification Protocol (IPM-VP) that our regressions should yield CV(RMSE)s (coefficients of variation of the root mean square of the error), below a certain level in order for the regression to be considered statistically significant. But what happens if you have a large portfolio, such as a school district? Is it necessary that every meters' regression have a CV(RMSE) conforming to this rule? This paper suggests that individual meters' CV(RMSE)s do not matter. What matters is the portfolio's overall CV(RMSE). We tested this theory on a sample of 236 meters and found that the CV(RMSE) of the portfolio can be more than 50% lower than the average CV(RMSE) of the individual meters.

BACKGROUND

In previous articles, I have questioned whether the CV(RMSE) and the coefficient of determination (R^2) are useful indicators of whether a regression model (or fit) is statistically significant. The general consensus of the experts is that the R^2 value should be ignored, and the CV(RMSE) should be lower than a threshold for a fit to be considered acceptable.

A simplified, but not entirely accurate, definition of the CV(RMSE) is that it is a measure of scatter around a regression fit line (see following equation). A CV(RMSE) of 10% means the average distance between a point and the fit line is 10% of the fit line.

The official definition of CV(RMSE) is: $CV(RMSE) = \frac{1}{\bar{y}}\left[\frac{\sum(y_i - \hat{y}_i)^2}{n-p}\right]^{0.5}$

where:

- n is number of bills
- p is number of independent variables used in regression + 1
- y_i represents the actual bill
- $\hat{y}_i$ represents what the fit line estimates the month's bill to be
- $\bar{y}$ represents the average bill during the base year

EVO (Efficiency Valuation Organization) recommends that linear regressions have a CV(RMSE) that is less than one half of the expected savings fraction. In other words, if you expect to save 25% of the total energy usage of a meter, then your CV(RMSE) should be 12.5% or less.

The American Society of Heating, Refrigeration, and Air-Conditioning Engineers (ASHRAE) produced Guideline 14 that recommended that linear regressions having CV(RMSE) values less than 25% are acceptable*†.

In the past I have questioned using CV(RMSE) as a means of deciding whether a linear regression model is acceptable to use or not. Recently, Professor Eric Mazzi wrote that many in the statistics community are starting to question the value of R^2 and CV(RMSE) as measures to determine whether to use a regression model or not. "Statistically significant" is becoming an outmoded term.‡ So, perhaps I am not alone on this point after all. It appears others are realizing this as well.

Regardless, in this article, I will assume that EVO's the CV(RMSE) guidance holds, and we want the CV(RMSE) to be less than or equal to half the expected savings fraction.

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*Actually, ASHRAE 14-2014 says: "the baseline model shall have a maximum CV(RMSE) of 20% for energy use and 30% for demand quantities when less than 12 months' worth of post-retrofit data are available for computing savings. These requirements are 25% and 35%, respectively, when 12 to 60 months of data will be used in computing savings. When more than 60 months of data will be available, these requirements are 30% and 40%, respectively."

†ASHRAE 14 also requires that the fractional savings uncertainty (FSU) be less than 50% of the annual savings at 68% confidence.

‡Mazzi, Eric, "Commentary on Article 'Statistics and Reality—Addressing the Inherent Flaws of Statistical Methods Used in Measurement and Verification," *International Journal of Energy Management*, Volume 4, Issue 2, 2022.

PURPOSE OF THE ARTICLE

Instead of challenging the appropriateness of using CV(RMSE) to determine whether a fit is statistically significant, we want instead to point out that in cases where there is a portfolio of meters, holding each individual meter to the CV(RMSE) standard may not be necessary at all.

To address this problem, I took a large data set and calculated CV(RMSE)s at the meter level and at the portfolio level and compared the two.

MY DATA

Having worked in utility bill analysis for over 25 years, I have some large data sets of monthly bills. In the past, I was blessed with tracking several big box store chains, one of which had 2500 meters. We performed regressions on all of these meters and estimated energy savings for our clients.

In particular, I have a data set of electricity meters for the now defunct Circuit City stores in the Eastern half of the United States. There are 263 meters in this data set.

Years ago, we performed regression analysis on the meter data versus cooling degree days (CDD). We deselected some outliers, many of which were estimated/actual bills.†‡ I have since then reincluded all of the outliers, so that I could have some bad fits in my data set. The worst fit in the group was for the Midlothian Virginia store. The fit provided me with a CV(RMSE) of 22.2% and an R^2 of 0.227. Let's take a look at this meter. It would actually be a good fit if I wouldn't have reinserted the estimated and actual bills back into the regression. In Figure 1, you can see the estimated bill is well below the fit line and the actual bill, well above it. Estimated actual bills compromise the quality of fits, decreasing R^2 values and increasing CV(RMSE)s.

In Figure 2, the blue dots represent bills, and the red line is what the regression equation predicts that the bills should be, based on the regres-

†Estimated/Actual refers to cases where the utility does not read a meter one month, and instead estimates what the bill should be. Invariably, this "estimated" bill is low. They then follow that bill up, the next month, with an "actual" bill, which is a real reading, but is high, as it contains the second month's usage plus the underage from the first month.

‡I know, there are better ways to handle this. Today, I would combine the two bills into one, and then the combined bill would probably lie right on the regression line. But I wanted to have some bad fits in my sample.

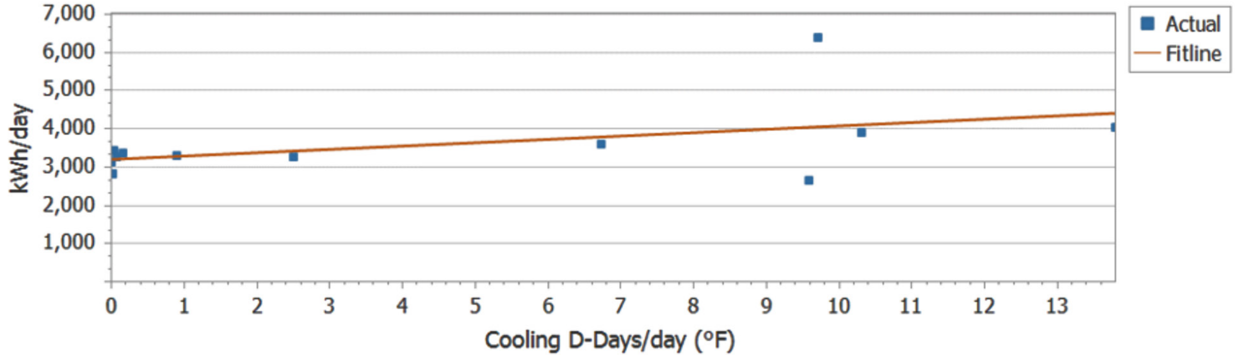


Figure 1. Linear Regression of Midlothian, VA store kWh/day vs. CDD/day

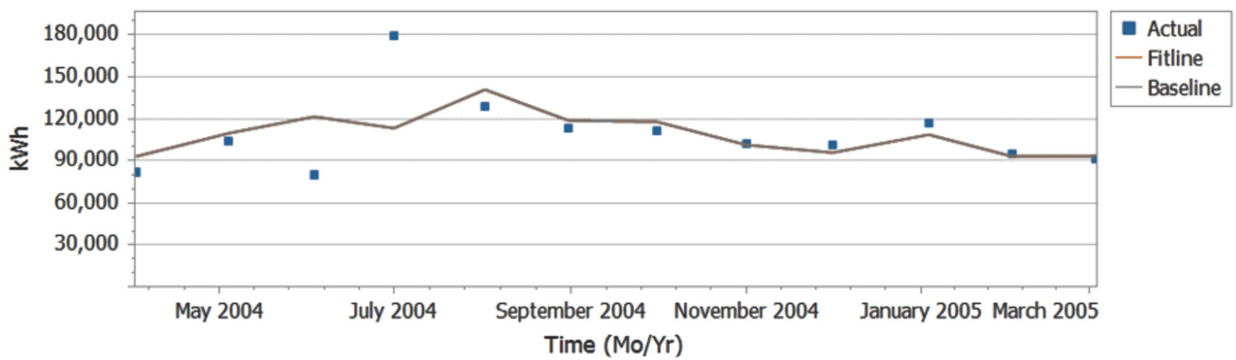


Figure 2. Linear Regression results of Midlothian, VA store kWh/day vs. CDD/day presented as kWh vs. time

sion equation. You can see that the estimated bill is in June and the actual bill in July.

OVERALL NATURE OF DATA

On average, as evidenced by the low CV(RMSE) values and the high R^2 values, the regressions were of high quality, better than you would expect. I suppose that implies that the building controls worked fairly well. In other words, the building responds in a predictable manner to weather conditions.

The average R^2 value of the 238 meters is 0.78, with a standard deviation of 0.20. The average CV(RMSE) of the 238 meters is 5.2%, with a standard deviation of 3.0%. Figures 3 and 4 present histograms to give you an idea of the spread of CV(RMSEs) and R^2 values. The horizontal lines represent the average values.

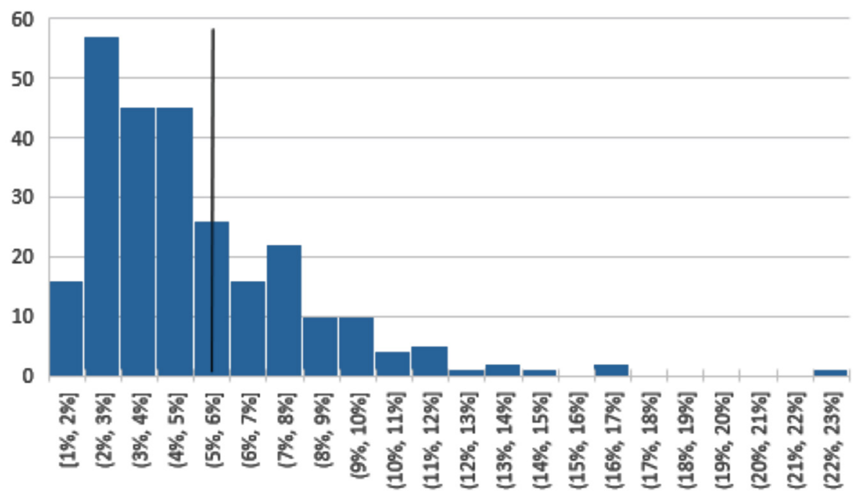


Figure 3. Histogram of CV(RMSE) from the regressions of kWh/day vs. CDD/day of all 238 stores

MY EXPERIMENT

The purpose of this experiment was to determine to what extent the CV(RMSE) of the entire portfolio was different than the average CV(RMSE) of the individual meters. And how does the number of meters in the sample affect the portfolio CV(RMSE)?

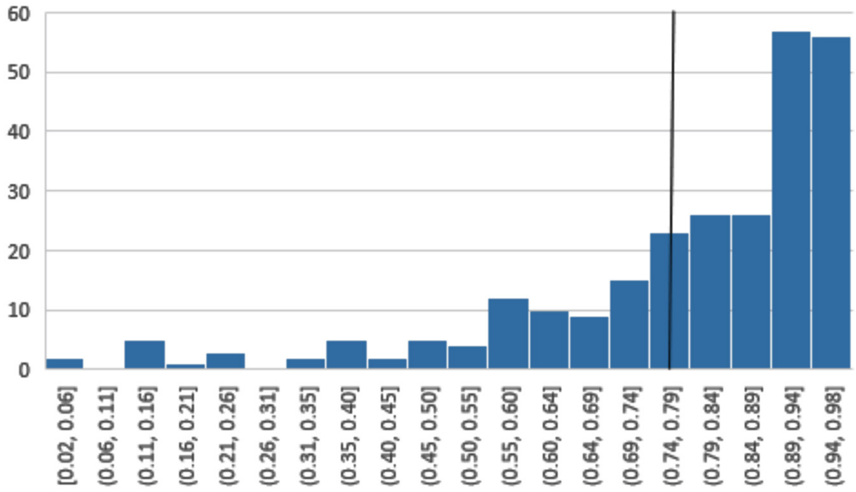


Figure 4. Histogram of R^2 from the regressions of kWh/day vs. CDD/day of all 238 stores

I had 235 regression equations, their associated CV(RMSE)s and R^2 values. For each of the 12 months in the base year period I had 235 actual bills and 235 adjusted baselines (which is what the regression equation predicts the usage should have been). Table 1 presents a snippet of actual bill data for a small number of meters. For the sake of space, I did not show all 12 months.

Table 1.
A Few Months of Sample Actual Bill Data for the Base Year Period

Meter	Mar	Apr	May	Jun	Jul
Harrisonbrg VA $1600-E	60,672	72,960	84,864	80,640	72,576
Fredrcksbrg VA #1601-E	71,040	84,880	90,720	99,520	97,200
Tyler TX #1602-E	48,236	55,263	69,086	73,349	78,676
Longview TX #1603-E	46,200	51,760	47,440	61,240	72,760
Chrltsvl VA #1604-E	62,240	68,560	81,600	72,320	80,800
Jacksonvill NC #1607-E	69,100	75,600	81,300	102,400	107,600
Wilmington NC #1608-E	62,700	65,100	75,700	93,900	93,300
Temple TX #1611-E	49,936	59,673	57,673	71,153	68,422
Killeen TX #1612-E	75,282	71,544	81,289	90,093	86,742
Bogart GA #1615-E	71,820	57,420	92,940	86,820	99,480

For each month in the base year period, I summed the actual bills and adjusted baselines. The sums are presented in Table 2. Again, I only showed a few months due to space limitations.

Table 2.
A Few Months Summation of All Data for 235 Meters for the Baseline Period

	Mar	Apr	May	Jun	Jul
Adjusted Baseline	18,083,474	19,105,442	21,012,420	22,734,902	23,316,373
Actual	17,850,320	18,797,116	20,992,189	22,841,431	23,502,629
Error	233,154	308,326	20,231	-106,529	-186,256
%	1.3%	1.6%	0.1%	-0.5%	-0.8%

I calculated CV(RMSE) of this summation. I called it the Portfolio CV(RMSE).

I then started removing meters from the sample. I repeated this calculation of Portfolio CV(RMSE) for the first 200 meters, the first 150 meters, the first 100 meters, on down to the first 2 meters.

Table 3 presents the results, along with average R^2 values.

Table 3.
Trial 1: Meters, Average R^2, Average CV(RMSE), Portfolio CV(RMSE), and Reduction in CV(RMSE)

# Meters	Average R^2	Average Individual CV(RMSE)	CV(RMSE) of Portfolio	Percentage Reduction in CV(RMSE)
235	0.78	5.3%	1.6%	70%
200	0.78	5.3%	1.5%	71%
150	0.78	5.3%	1.5%	71%
100	0.78	5.4%	1.7%	69%
50	0.82	4.7%	1.7%	64%
25	0.81	5.2%	2.3%	55%
15	0.80	5.4%	2.9%	46%
10	0.84	4.6%	2.9%	37%
5	0.81	4.8%	3.3%	31%
4	0.87	4.5%	3.0%	34%
3	0.86	4.6%	3.1%	34%
2	0.89	3.3%	3.0%	10%
1	0.94	2.0%	2.0%	0%

To a degree, these results were due to the particular order of the meters listed. For example, the meters with the lowest CV(RMSE) could have been the first ones I eliminated, leaving the higher CV(RMSE) meters. This could unfairly bias the results. To avoid this problem, I repeated this procedure four times. For each of these trials, I mixed the order of the meters.*

RESULTS

For all 235 meters, we found that the CV(RMSE) dropped from 5.3% (the average of the individual meters) to 1.6% (the CV(RMSE) of the portfolio as a whole), a 70% improvement. In the first trial, in order to see a 50% improvement in CV(RMSE), we would need the portfolio to include about 17 meters. In the other trials, to get to a 50% improvement in CV(RMSE), we would need to have about 4, 8 and 20 meters. This is all shown in Table 4, which presents the reduction of portfolio CV(RMSE) from the average individual CV(RMSE).

Table 4.
Reduction in CV(RMSE) from Average (CVRMSE) for All Four Trials Using Weather Normalization

# Meters	Trial 1	Trial 2	Trial 3	Trial 4	Average Reduction
235	70%	70%	70%	70%	70%
200	71%	70%	69%	71%	70%
150	71%	70%	66%	70%	69%
100	69%	68%	65%	72%	68%
50	64%	60%	67%	74%	66%
25	55%	58%	56%	69%	60%
15	46%	62%	45%	63%	54%
10	37%	55%	48%	53%	48%
5	31%	53%	35%	39%	40%
4	34%	50%	18%	38%	35%
3	34%	33%	18%	35%	30%
2	10%	12%	10%	28%	15%
1	0%	0%	0%	0%	0%

*Ideally, I would try it with 100 or more different combinations of meters, but I don't think the added time would bring us any additional knowledge. The outcome I got in both cases confirmed my guess as to what would happen.

We calculated the reduction in CV(RMSE) as follows.

Reduction % = (Average Meter CV(RMSE) – Portfolio CV(RMSE))/ Average Meter CV(RMSE)

The trends are clearer in the graphical representation, as shown in Figure 5. The thick line with no markers represents the average of the four trials.

Figure 6 presents the data at the lower range, because that is where it is more interesting. On average, it took about 11 meters to drop the CV(RMSE) by 50%, and 25 meters to drop the CV(RMSE) by 60%.

Although we are using the same data, the meters are mixed up in different orders, so each trial effectively represents a different data set. The trials provide different results because the meters in each collection of X meters are different in the different trials. Although every data set will provide different results, we can make a generalization.

It is clear that the CV(RMSE) of the portfolio will be much lower than the average CV(RMSE) of the individual meters. A 50% reduction in CV(RMSE) is likely. But just how many meters is required to see a 50% drop in CV(RMSE)? That will depend on your data set.

WHY DOES THE PORTFOLIO DROP THE CV(RMSE)?

The reason more meters tend to dampen the CV(RMSE) is that the randomness in the bills tends to smooth out as more meters are added to the sample. But this is not always the case.

ARE THERE EXCEPTIONS?

Suppose you have a portfolio of 100 schools all of which use electricity to cool. Suppose you didn't do a regression at all for these meters, and instead used an average kWh/day to represent baseline energy usage. Over the course of a year, it would even out. The kWh/day model will end up with the same number of kWh as the summation of the bills over the course of a year. The mean bias error would be 0. But on a monthly basis, the average kWh/day model would estimate low usage in summer and high usage in winter. Figure 7 represents this concept pictorially. The "fit line" represents the kWh/day model's prediction of the monthly amounts.

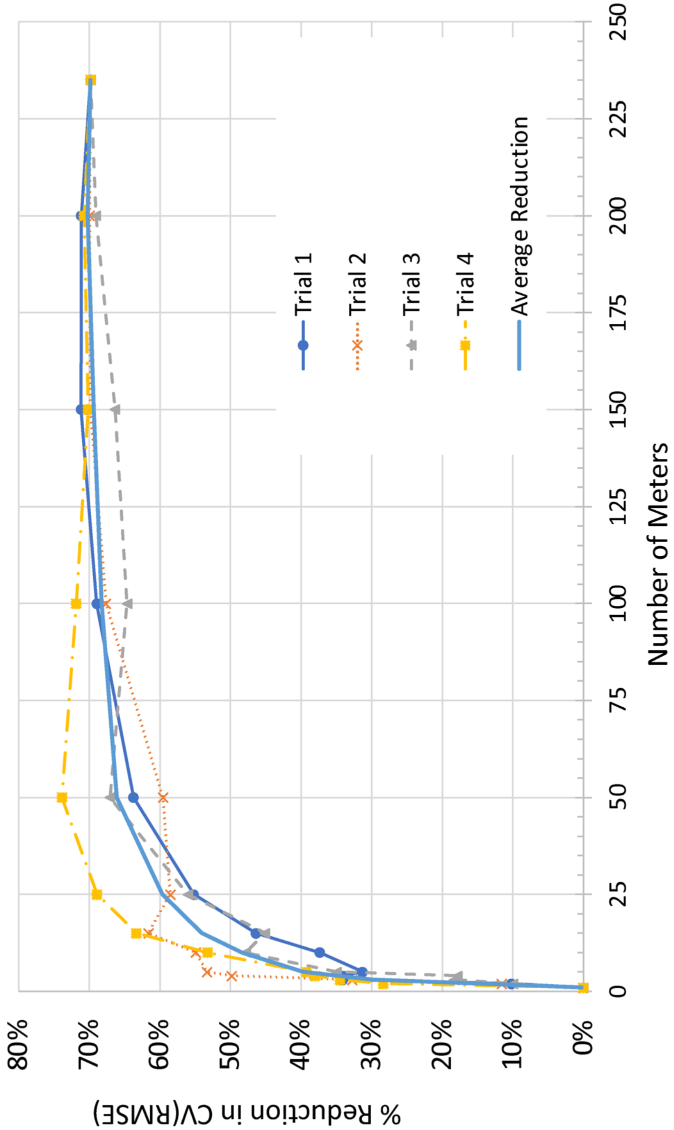


Figure 5. Percent Reduction in CV(RMSE) from Average (CVRMSE) vs. Number of Meters in Portfolio for All Four Trials Using Weather Normalization

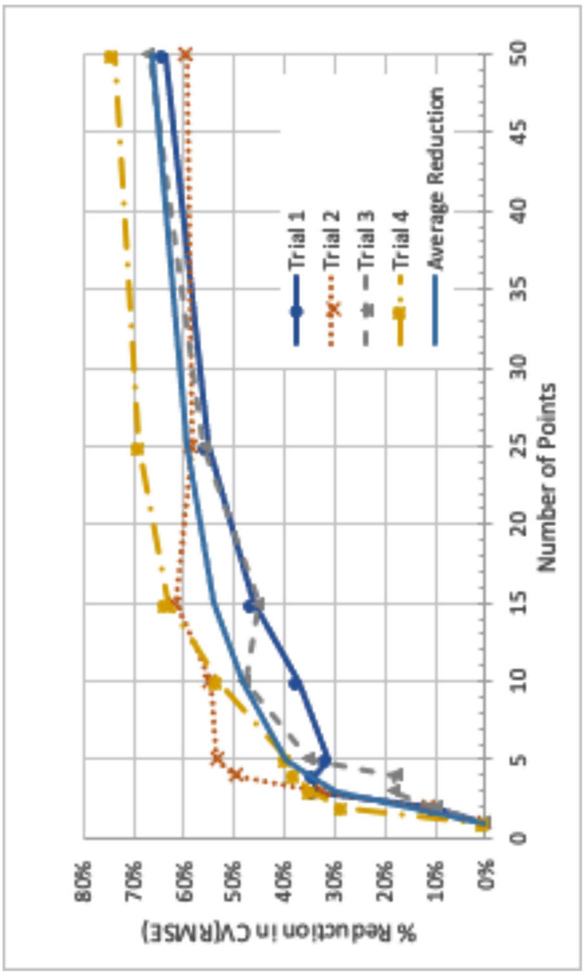
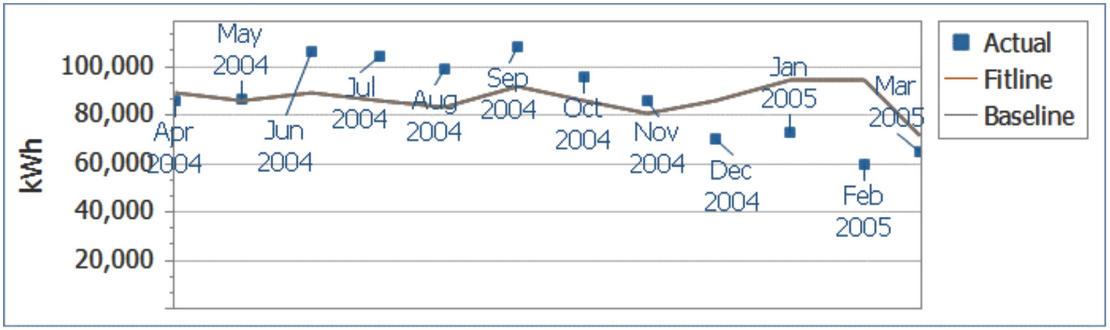


Figure 6. Percent Reduction in CV(RMSE) from Average (CVRMSE) vs. Number of Meters (for up to 50 meters) in Portfolio for All Four Trials Using Weather Normalization



12 bills spanning Mar 14, 2004 to Mar 10, 2005

Weather location: DALLAS-FORT WORTH, TX, USA

kWh = 2,872.768×#Days

CVRMSE = 19.79%
R2 = 0.000
SE = 17,154

Figure 7. Average kWh/day model (fit line) prediction of monthly usage versus actual monthly usage.

What would happen if we didn't do regressions on any of the meters in our Circuit City sample and then performed the same test?

Would the CV(RMSE)s drop, as they did in our other example?

To save time, I didn't use all 235 meters. Instead, I took the 61 stores whose names started with an "A," "B," or "C." Like before I randomized the order of the meters and took four trials, comparing average individual CV(RMSE) with portfolio CV(RMSE). Table 5 and Figure 8 presents the reduction of portfolio CV(RMSE) from the average individual CV(RMSE).

The average CV(RMSE) of these 61 stores was 12.8%. I then calculated the CV(RMSE) of the entire portfolio of the 61 stores, and got 11.2%, a reduction of only 12%. Compare that to my earlier trials. When I performed linear regressions of kWh/day versus CDD/day, at 50 meters, I had an average reduction in CV(RMSE) of 66%. That is a big difference.

As before, there is variation in the average meters' CV(RMSE) and the Portfolio CV(RMSE), depending on which meters are in the sample. However, overall, on average, it is clear that the measuring CV(RMSE)s at a portfolio level drops the CV(RMSE), but in this case, the CV(RMSE) did not drop by much.

So why did the CV(RMSE) of the portfolio not drop substantially in this case when I didn't do regressions to weather?

If a regression is perfect, that is, all points are on the line, the CV(RMSE) would be zero. In our regressions, we found good fit lines, high in the summer, low in the winter, just like the bills. Because there was so little scatter, our CV(RMSE)s were low.

When we didn't do a regression and just took the average kWh/day, we expected high CV(RMSE)s because the fit line was much higher than the winter bills and much lower than the summer bills. There was always going to be scatter. By combining the un-regressed meters together, we may have smoothed some of the scatter (hence the 12% reduction in CV(RMSE). But the general tendency of overestimating usage in the winter and underestimating usage in the summer was only reinforced because all of the meters had this same pattern. The summation of the average kWh/day models still overestimated usage in the winter and underestimated usage in the summer, which leads to higher scatter and thus higher CV(RMSE) at the portfolio level.

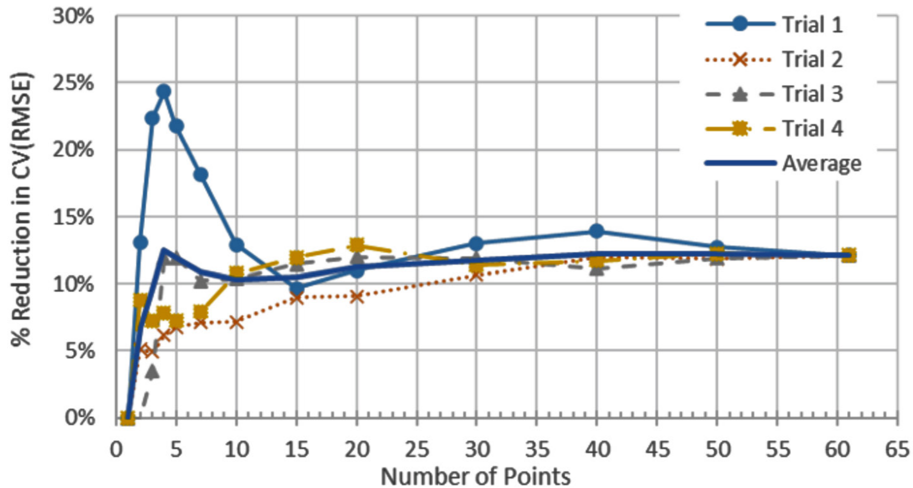


Figure 8. Percent Reduction in CV(RMSE) from Average (CVRMSE) vs. Number of Meters in Portfolio for All 4 Trials Using an Average kWh/day Model (as Opposed to Weather Normalization)

Table 5.
Reduction in CV(RMSE) from Average (CVRMSE) for All Four Trials Using Average kWh/Day Model

Number of Meters	Trial 1	Trial 2	Trial 3	Trial 4	Average Reduction
61	12%	12%	12%	12%	12%
50	13%	12%	12%	12%	12%
40	14%	12%	11%	12%	12%
30	13%	11%	12%	11%	12%
20	11%	9%	12%	13%	11%
15	10%	9%	11%	12%	11%
10	13%	7%	10%	11%	10%
7	18%	7%	10%	8%	11%
5	22%	7%	12%	7%	12%
4	24%	6%	12%	8%	13%
3	22%	5%	3%	7%	10%
2	13%	5%	0%	9%	7%
1	0%	0%	0%	0%	0%

Note: In Trial 1 of the average kWh/day models, we saw some high reductions in CV(RMSE) when the samples had 3 to 7 meters. This was due to a couple of meters having very low CV(RMSE)s. This aberrant behavior only reinforces the idea that the magnitude of CV(RMSE) reduction has much to do with the characteristics of the individual meters' fits.

CONCLUSIONS

The IPMVP is suggesting that when using regression analysis as part of the Option C M&V process, the CV(RMSE) for each meter should be less than 50% of the expected savings fraction. In other words, if you expect to save 20% on a meter, then the CV(RMSE) should be less than 10%.

When performing regressions on a portfolio of buildings, such as a school district, the CV(RMSE) of each individual meter may not be that important. What perhaps may be more important is the CV(RMSE) of the portfolio of meters, which will likely be much lower than the CV(RMSE) of the individual meters.

For energy service companies (ESCOs) performing Option C M&V

on a school district, a military base, or another portfolio of meters, perhaps the overall portfolio CV(RMSE) should be considered, rather than the CV(RMSE) of each meter. That would allow the M&V practitioner more latitude to include regressions with poor fits in the portfolio.

Ideally, the ESCO would calculate the CV(RMSE) of the portfolio and use that to evaluate the reasonableness of the collection of regression models.

This is not an original idea. CalTRACK, a collaboration of M&V specialists developed a set of guidelines for utilities when using Option C M&V methods.* CalTRACK was well aware of the fact that CV(RMSE)s drop at the portfolio level. CalTRACK has recommended that CV(RMSE)s of individual meters in a portfolio could be as high as 100%. That means, in my sloppy lay language, that the average point could be 100% away from the fit line. That is a remarkably low bar to overcome!

We are not suggesting adopting the 100% rule. Rather, the CV(RMSE) should be evaluated at the portfolio level and not at the meter level.

AUTHOR BIOGRAPHY

John Avina, CEM, CEA, CMVP, CxA, has worked in energy analysis and utility bill tracking for over 25 years. During his tenure at Thermal Energy Applications Research Center, Johnson Controls, SRC Systems, Silicon Energy and Abraxas Energy Consulting, Mr. Avina has managed the measurement and verification (M&V) for a large performance contractor, managed software development for energy analysis and M&V applications, created M&V software that is used by hundreds of energy professionals, taught over 250 energy management classes, created hundreds of building models and utility bill tracking databases, modeled hundreds of utility rates, and has personally performed energy audits and RCx on over 25 million square feet. Mr. Avina currently chairs the Certified Energy Auditor Exam Committee for the Association of Energy Engineers. Mr. Avina has a MS in Mechanical Engineering from the University of Wisconsin-Madison. John may be contacted via email at john.avina@abraxasenergy.com.

*See the CalTRACK website for more information at caltrack.org.

Dynamics of the Global Electric Vehicle Market

Ronald L. Miller, PE, CEM, REP

ABSTRACT

The de-carbonization of our modern global society is moving forward at a rapid pace, with increased renewable energy supplies and the replacement of internal combustion engines (ICE) with electric vehicles (EV). The EV market will be driven by 1) EV power demand, 2) capacity planning for generation and grid improvements, 3) market leader advantages, 4) key minerals required and their location, and supply chain constraints, and 5) the advantages for one country to lead EV development. Identifying the *what, why, and how* of this dynamic changeover will be key for business leaders as they anticipate, understand, and exploit to improve their business during the future acceleration toward EVs.

EV POWER DEMAND MODELING

As governments and businesses evaluate the changeover from the internal combustion engine (ICE) to electric vehicles (EVs), the impact of this energy transition must be modeled and identified. If every car and truck using petroleum products in the United States (U.S.) were converted to an EV, the country would see a huge spike in electricity demand, along with the attendant spike in generation, transmission, and distribution capacity, all at a huge capital cost.

In 2019, the U.S. used 12.091 million barrels of oil per day for gasoline and distillate demand, or an equivalent of 2.8 million gigawatt-hours (GWh) of electricity, as shown in Figure 1.

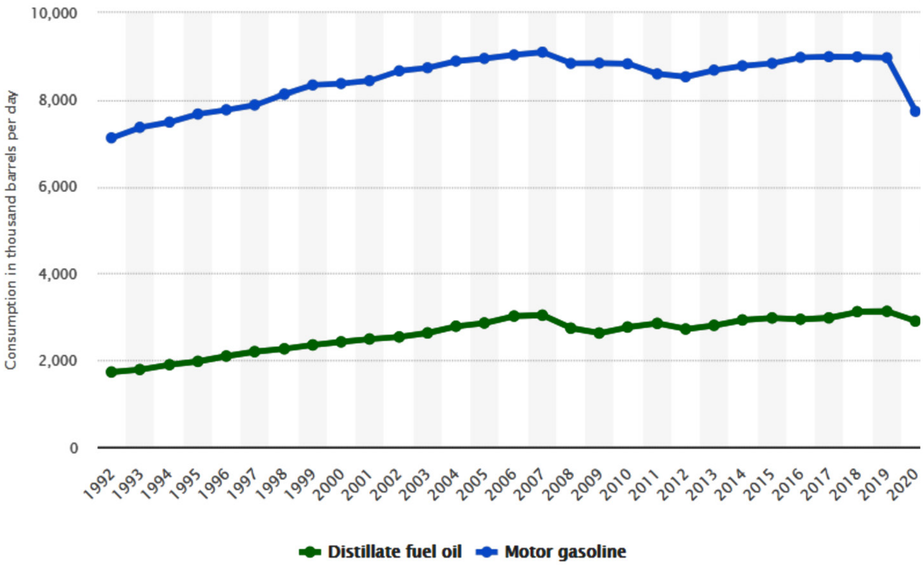


Figure 1. U.S. Gasoline and Distillate Demand History 1992-2020
(Source: https://www.statista.com/statistics/189410/us-gasoline-and-diesel-consumption-for-highway-vehicles-since-1992/)

CAPACITY PLANNING FOR GENERATION AND GRID IMPROVEMENTS

Comparing the last representative electricity demand year (2019), the U.S. used 3.9 million GWh of electricity for industrial, commercial, and residential demand, as shown in Figure 2.

To facilitate the electrification of our transportation fleet, an additional 72% of incremental electricity generation must be created, along with the attendant 72% increase in transmission and distribution infrastructure. As the U.S. moves toward more renewable energy in its energy mix, and additional capital expenditure will be required for energy storage to bridge the timing of renewable energy production and energy demand.

This estimate does not include the electrification of our current heating infrastructure whereby natural gas combustion for heating at home and businesses would be replaced by electrical heat.

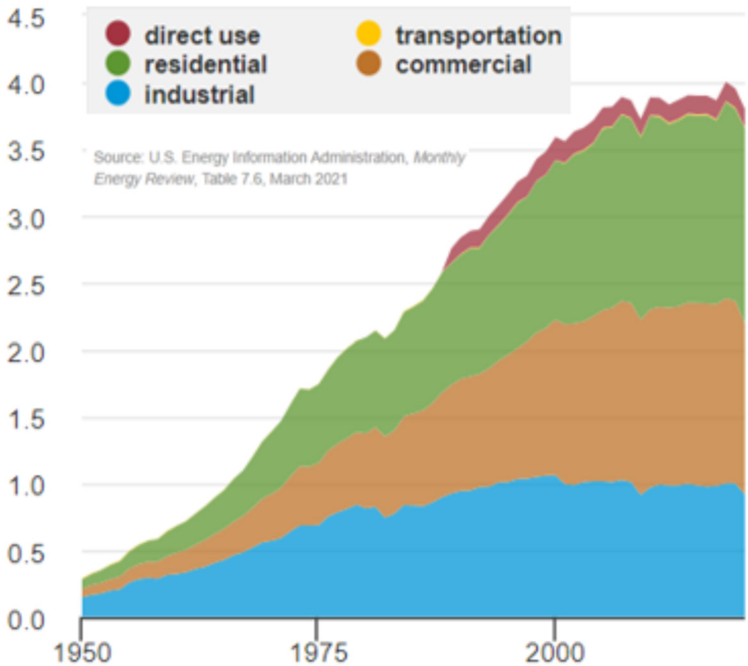


Figure 2. U.S. Electricity Demand History 1950-2020
(Source: U.S. Energy Information Administration (EIA). Monthly Energy Review, March 2021. DOE/EIA-0035(2021/3), page 142. Available at https://www.eia.gov/totalenergy/data/monthly/archive/00352103.pdf. Accessed October 17, 2022.)

MARKET LEADER ADVANTAGES

The key advantages China currently enjoys in its quest for world EV production and cost leadership are the following:

1. Economies of scale
2. Swift autocratic policy decisions
3. Battery raw materials control
4. Domestic coal supply and low-cost coal electricity production.

Economies of Scale

China's economy has seen tremendous change over the last 20 years, averaging a compounded annual 14.2% growth rate. With this domestic growth engine for a large population of 1.4 billion, average per capita incomes have increased by a 20-year compounded annual rate of 10.72%. Increasing prosperity with more of its people wanting greater mobility, has provided China with a huge domestic market for EVs. In 2021, over half of the global EVs were sold in China, as shown in Figure 3.

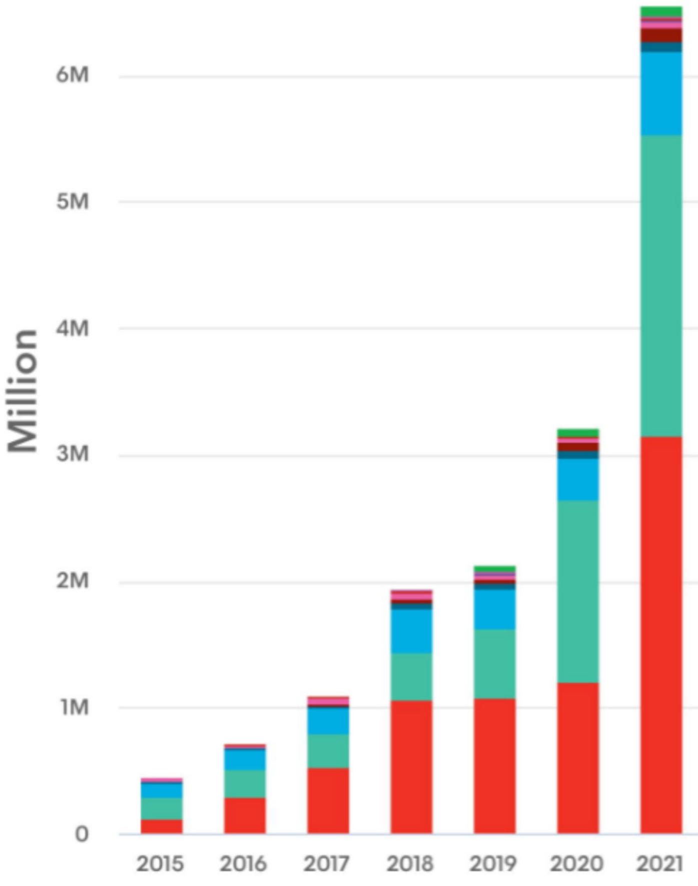


Figure 3. Global Plug-in Electric Car Sales, 2015 to 2021

(Source: International Energy Agency (IEA). Global electric car sales by key markets, 2010-2020, IEA, Paris. Available at https://www.iea.org/data-and-statistics/charts/global-electric-car-sales-by-key-markets-2015-2020. Accessed October 17, 2022.)

Swift, Autocratic Policy Decisions

The Chinese government is mandating more EVs at the expense of ICE vehicles compared to Western democracies, while reducing the number of licenses available for gasoline-powered cars. This policy from the top, President of the Republic of China, Xi Jinping, will increase demand for EVs leading to greater EV production, larger economies of scale, and lower unit production costs. This will enable China to gain a world-wide marketing advantage. In the Chinese system, no Act of Congress, debate, or negotiations with the Environmental Protection Agency is necessary, so quick, decisive action to provide advantages to China are implemented.

Battery Raw Material Controls

China now has a tight grip on the global supply of the elements needed to manufacture batteries from four components: anode, cathode, separator, and electrolyte. China currently controls between 50% and 77% of the global market for the raw materials of these components, according to Yano Research Institute (www.yanoresearch.com). A key element of an electric vehicle's price is the cost of its batteries, and China already makes more than half of the world's electric vehicle batteries, as shown in Table 1.

Table 1. Lithium-Ion Manufacturing Capacity

Rank	Country	Percent of World Total
1	China	79.0%
2	United States	6.2%
3	Hungary	4.0%
4	Poland	3.1%
5	South Korea	2.5%
6	Japan	2.4%
7	Germany	1.6%
8	Sweden	0.6%
9	United Kingdom	0.3%
10	Australia	0.1%

Source: S&P Global Market Intelligence, data as of February 2021.
(https://www.visualcapitalist.com/sp/mapped-ev-battery-manufacturing-capacity-by-region/)

China controls more lithium reserves and much greater lithium production than the U.S., and in 2018, Chinese lithium production was 8,000 metric tons, third among all countries and nearly ten times U.S.

lithium production. Researching the capital devoted to lithium over the past few years, over 50% has been by the Chinese.

Domestic Coal Supply and Low-Cost Coal Electricity Production

A key for EV production is cheap energy for manufacturing of the EV's components. China has a large, low-cost domestic coal supply, yet it also imports significant amounts of coal to supply its electricity generators to produce electricity very inexpensively, a key cost advantage for its heavy industry. Chinese electricity generation by source in 2019 is shown in Figure 4.

In contrast to Chinese dependence on coal for electricity (64.7%), the U.S. gets 27.61% of its electricity from coal-fired generation, a much more environmentally favorable position, albeit at a higher cost of energy.

To put China's coal use in perspective, from 2005 to 2009, China added the equivalent of the entire US coal generation capacity. From 2010 to 2013, it added 50% of the entire US coal generation. China burns 4 billion tons of coal a year; the US burns less than 1 billion; European Union (E.U.) burns about 0.6 billion. This volume of coal consumed in China represents about 9.12 billion tons of CO_2e emissions per year.

As China is building 250 GW of new coal plants in the 2020s decade, according to data from the U.S. Energy Information Administration, from the end of 2010 to the end of 2019, 49 GW of U.S. and E.U. coal plants were retired. As U.S. and E.U. air gets cleaner, China's air gets more polluted.

KEY MINERALS REQUIRED FOR EVs AND LOCATION

A typical EV requires six times the mineral inputs of a conventional car, while the electrification of vehicles will require a doubling of electricity production and infrastructure to deliver this increased energy to the distributed demand points for EV recharging.

In addition to EV-driven energy demand, since 2010 the average amount of minerals needed for a new unit of power generation capacity has increased by 50% as the share of renewables in new investment has risen.

The key minerals needed in huge future quantities for EVs include copper, lithium, nickel, manganese, cobalt, graphite, zinc, and rare earths. Figure 5 delineates the growth in demand for these key minerals.

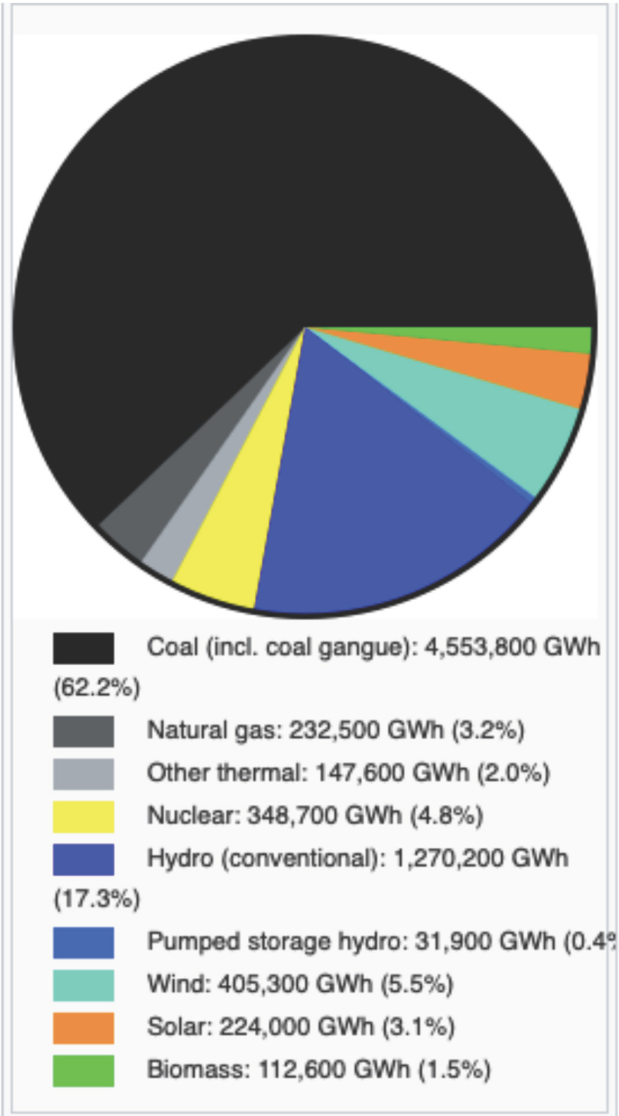


Figure 4. Chinese Electricity Generation by Source in 2019
(Source: https://en.wikipedia.org/wiki/Electricity_sector_in_China)

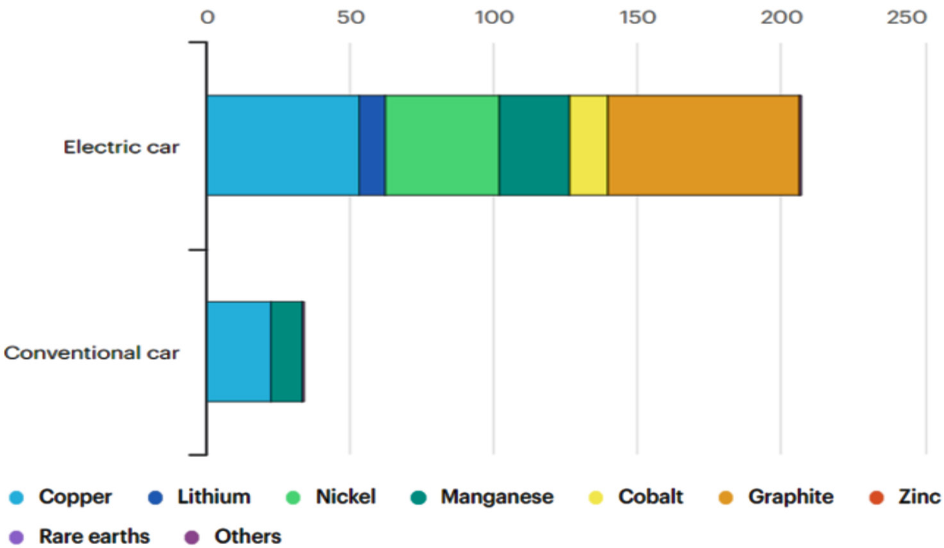


Figure 5. Minerals Used in EVs Compared to Conventional Cars (kg/vehicle) (Source: https://www.iea.org/reports/the-role-of-critical-minerals-in-clean-energy-transitions/executive-summary)

The types of mineral resources used vary by technology. Lithium, nickel, cobalt, manganese, and graphite are crucial to battery technology. Rare earth elements are essential for permanent magnets in wind turbines and electric vehicle motors, while copper is a "cornerstone" for all electricity-related technologies.

"If the world is to reach net zero by 2050, overall demand for critical minerals will increase by a factor of six," IEA Executive Director Fatih Birol said.* "The question is whether or not this can be met by production, our analysis shows there is a looming mismatch between the world's climate ambitions and the availability of critical minerals to realize those ambitions." "Many of the technologies the world will need to reach net zero require significantly more critical minerals than their fossil-fuel counterparts," Tim Gould, head of IEA's Division for Energy Supply, Outlooks and Investment, said.†

*IEA. The Role of Critical Minerals in Clean Energy Transitions. Part of World Energy Outlook, Flagship Report May 2021. Available at https://www.iea.org/reports/the-role-of-critical-minerals-in-clean-energy-transitions (accessed October 16, 2022).

†Ibid.

To achieve the 2040 Sustainable Development Scenario as described in the IEA report, four times the minerals will be required than are currently produced. Of that amount, an almost doubling of minerals for EVs and battery storage will be required from the present supply, as shown in Figure 6.

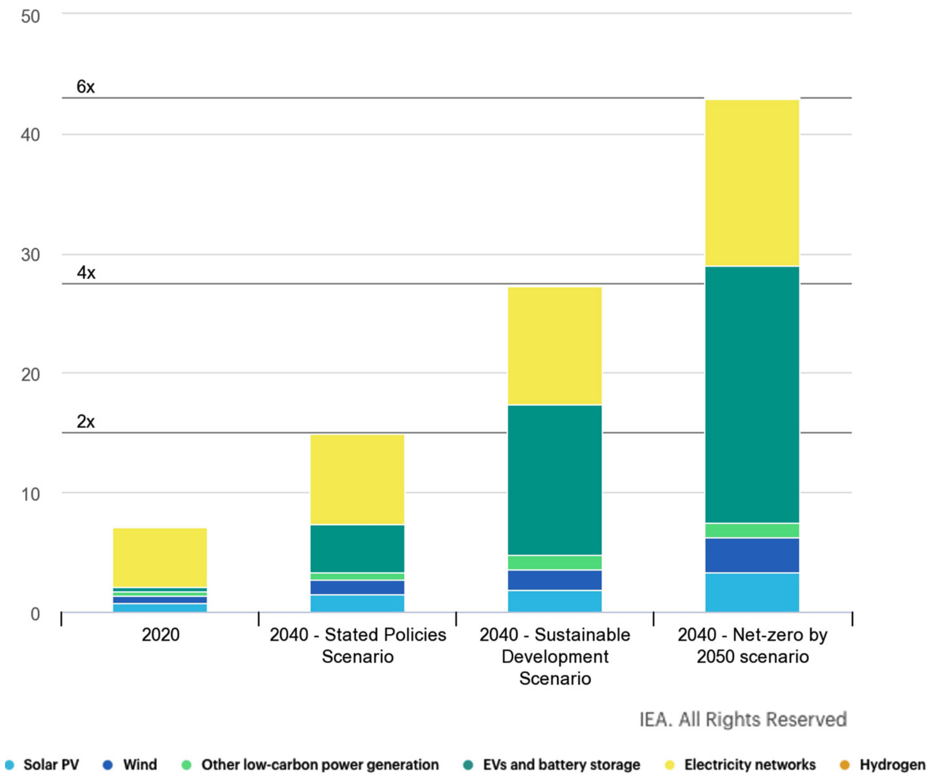


Figure 6. Total Mineral Demand for Clean Energy Technologies by Scenario, 2020 compared to 2040

(Source: https://www.iea.org/reports/the-role-of-critical-minerals-in-clean-energy-transitions/executive-summary)

Additionally, the incremental minerals are those that are not now in scaled-up production and in areas of the world where political stability could be an issue, as shown in Figure 7.

One of the key drivers for EV market development is the reduction in greenhouse gas (GHG) over the vehicle lifetime, as shown in Figure 8. The ICE car generates about twice the emissions over its lifetime than does a similar battery electric vehicle (BEV).

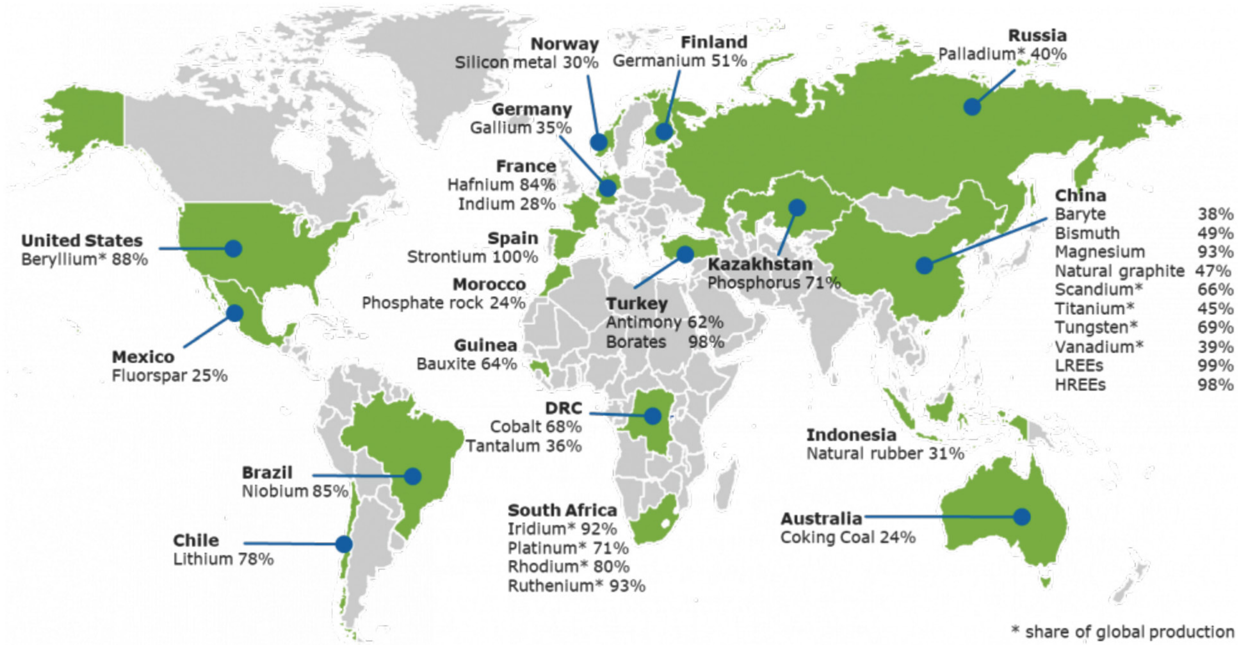


Figure 7. Global Locations of Key EV Mineral Supply

(Source: European Commission. Critical Raw Materials. Available at https://single-market-economy.ec.europa.eu/sectors/raw-materials/areas-specific-interest/critical-raw-materials_en. (Accessed on October 17, 2022).

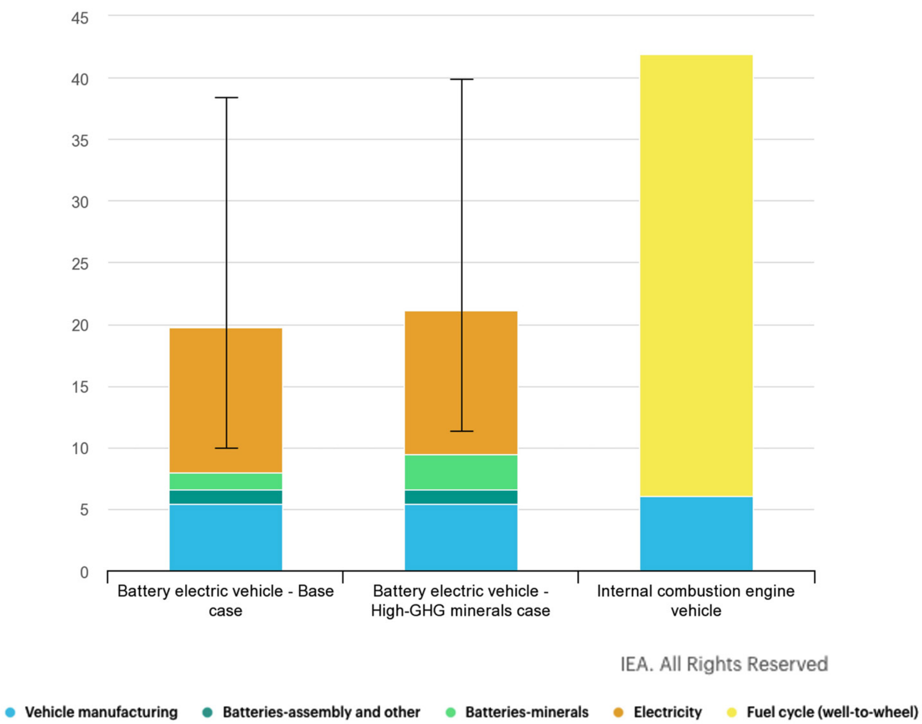


Figure 8. Comparative Life-cycle Greenhouse Emissions of a Mid-size BEV and ICE Vehicle (tons CO_2e per vehicle lifetime)
(Source: https://www.iea.org/reports/the-role-of-critical-minerals-in-clean-energy-transitions/executive-summary)

In May 2020, a World Bank Group report found that the production of minerals, such as graphite, lithium, and cobalt, could increase by nearly 500% by 2050, to meet the growing demand for clean energy technologies. It estimates that over 3 billion tons of minerals and metals will be needed to deploy wind, solar and geothermal power, as well as energy storage, required for achieving a below 2°C global temperature rise future.*

Batteries for EVs and renewable energy storage are the biggest factor driving the potential mineral shortage. An EV requires six times more

*The World Bank. "Mineral Production to Soar as Demand for Clean Energy Increases." Press Release May 11, 2020. Available at https://www.worldbank.org/en/news/press-release/2020/05/11/mineral-production-to-soar-as-demand-for-clean-energy-increases (accessed October 16, 2022.]

mineral resources than a car that runs on fossil fuels. Cobalt, nickel, graphite, and manganese are essential for batteries, too.

Although EVs reduce emissions by 50% over their lifetime, they require over 200 kilograms (kg) of minerals, or 6 times that for ICE, which require 35 kg, as shown in Figure 9.

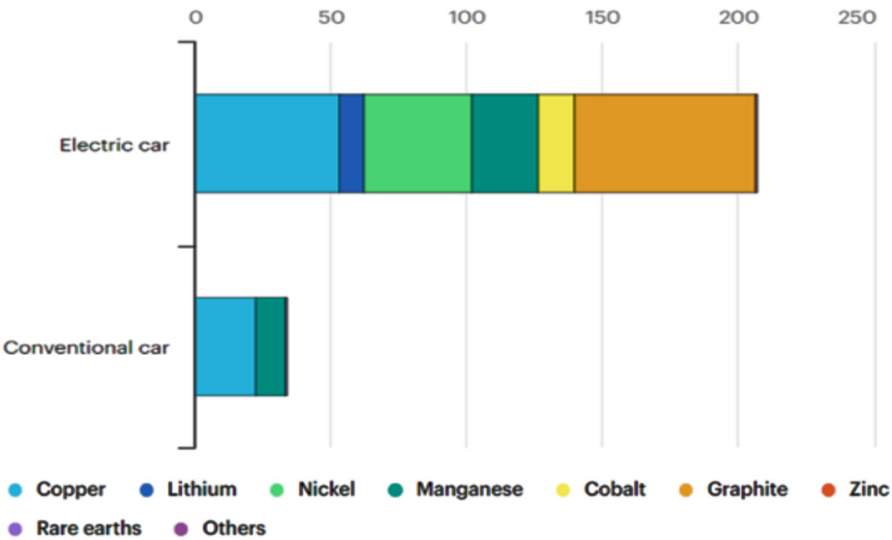


Figure 9. Mineral Demand for EV vs. ICE Vehicle (kg/vehicle)
(Source: https://www.iea.org/reports/the-role-of-critical-minerals-in-clean-energy-transitions/executive-summary. Accessed October 17, 2022.)

As the world embraces clean energy and EVs, it will see a tremendous increase in key mineral demand with multiples up to 6 times more than is currently produced to reach the 2050 net-zero scenario target, as shown in Figure 10. Mineral demand is shown in millions of tons.

As compared to oil and natural gas, the production of clean energy/EV minerals will be much more geographically concentrated in the future, as shown in Figure 11. This brings up potential concerns for rare earth sourcing concentration in China from both an environmental and future pricing standpoint. What impact will this concentration have on the geopolitical security of supply?

A graph from the U.S. Geological Survey provides a slightly different view of mineral supply concentration for clean energy/EV, as shown in Figure 12. It will be interesting in the future to gauge global comfort

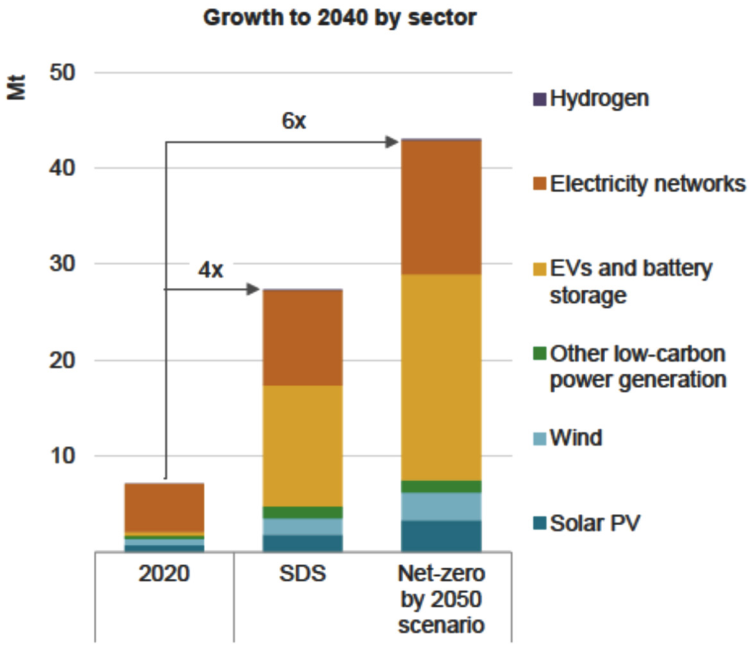


Figure 10. Clean Energy Mineral Demand Growth to 2040
(Source: IEA. The Role of Critical Minerals in Clean Energy Transitions. World Energy Outlook Special Report. IEA.org. May 2021. Available at https://www.iea.org/reports/the-role-of-critical-minerals-in-clean-energy-transitions. Accessed October 17, 2022.)

levels regarding reliable mineral supply source and stable pricing mechanisms from key producing countries, and whether it will be used as future geopolitical weapon like OPEC in 1970s.

Another way to view the geographical distribution of EV production is shown in Figure 13 with a heavy representation from China.

KEY MINERALS PRICES AND PRICE VOLATILITY:

As RE and EV minerals see increased demand, price volatility could be a key factor in the future, with Figure 14 depicting the price volatility from January 2020 to February 2021. How will price volatility of key minerals of 25 to 130% impact production/adoption of clean energy/EV products? Will EVs remain cost competitive to fossil fuels with potential future mineral price volatility and acceleration?

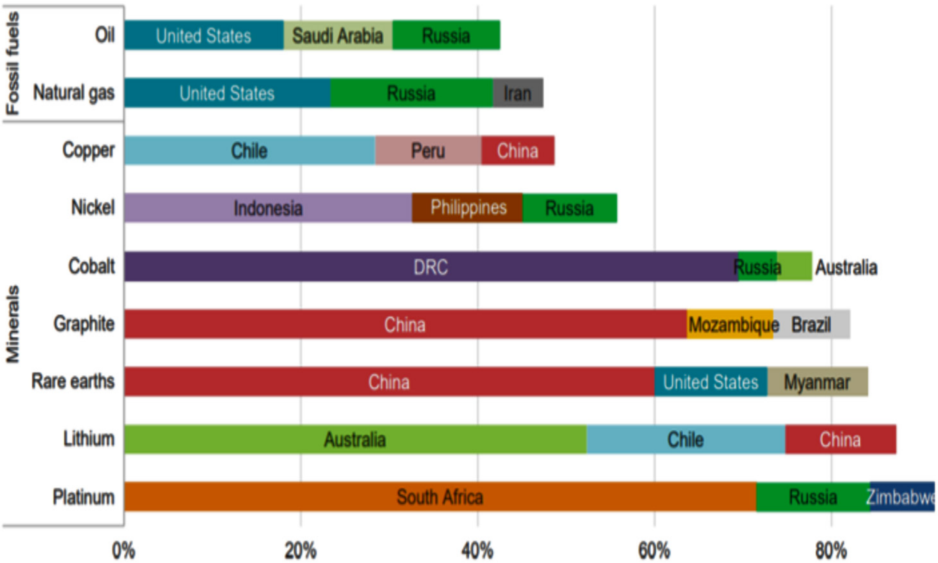


Figure 11. Mineral Supply Source in 2019
(Source: https://iea.blob.core.windows.net/assets/24d5dfbb-a77a-4647-abcc-667867207f74/TheRoleofCriticalMineralsinCleanEnergyTransitions.pdf. Accessed October 17, 2022.

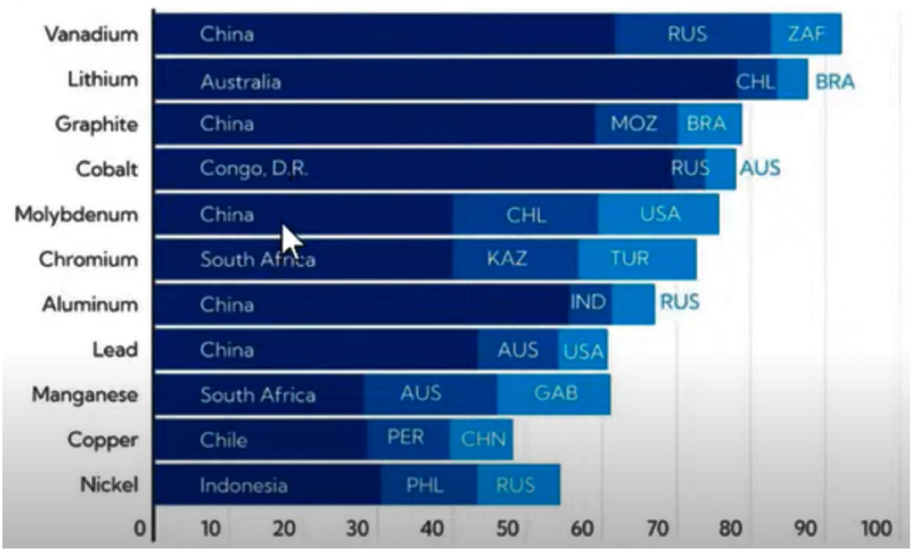


Figure 12. Minerals Crucial to Clean Energy and EVs
(Source: U.S. Geological Survey, Mineral Commodity Summaries 2021)

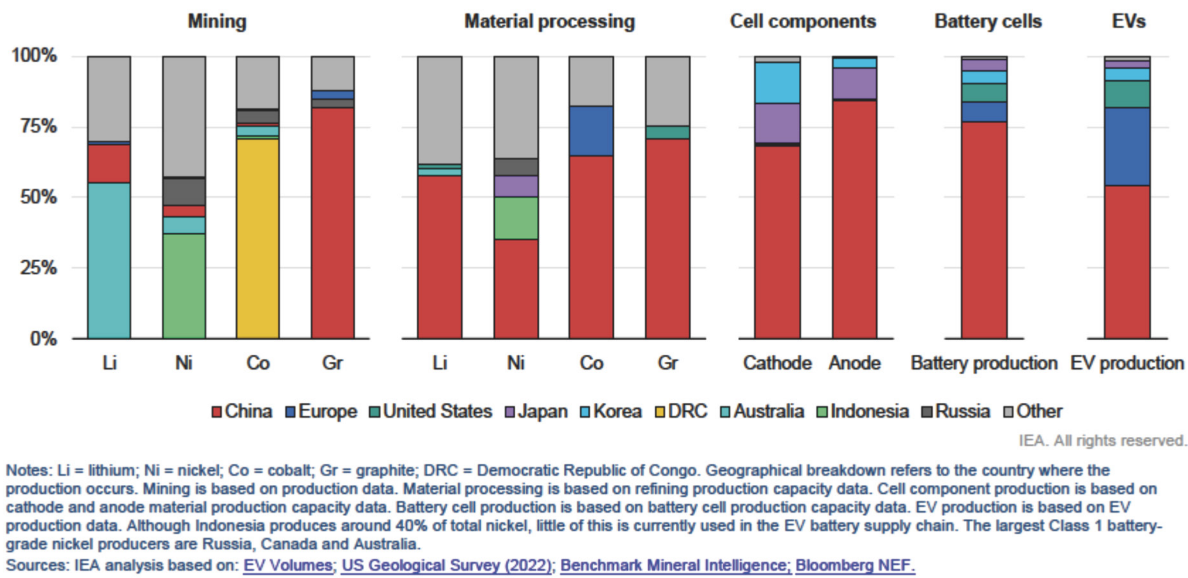


Figure 13.
Geographical Distribution of EV Production/Capacity by Supply Chain

(Source: IEA. Global EV Outlook 2022: Securing supplies for an electric future. May 2022. Available at https://www.iea.org/reports/global-ev-outlook-2022. Accessed October 17, 2022.)

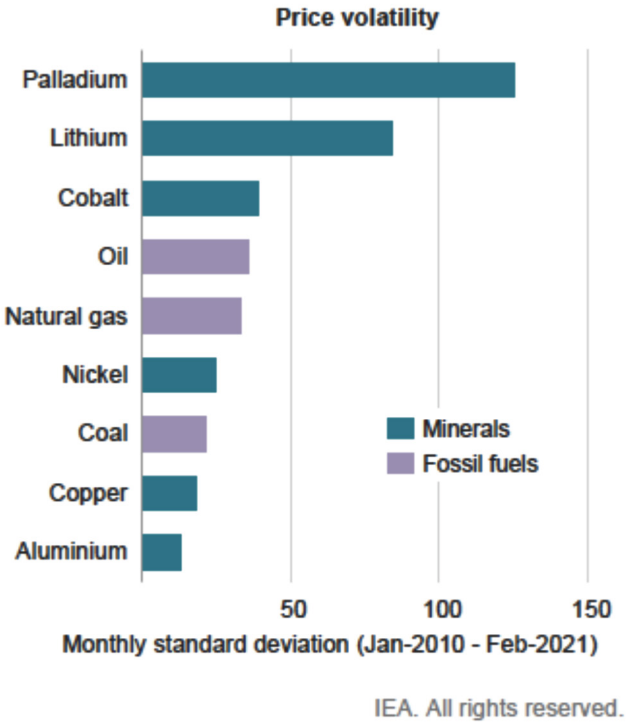


Figure 14. Clean Energy Mineral Price Volatility
(Source: IEA. The Role of Critical Minerals in Clean Energy Transitions. World Energy Outlook Special Report. IEA.org. May 2021. Available at https://www.iea.org/reports/the-role-of-critical-minerals-in-clean-energy-transitions)

To calibrate the RE and EV mineral price volatility, Figure 15 shows how key metal prices performed in 2021.

EV demand boomed, prices for battery metals (lithium skyrocketed by almost 500%).

KEY DRIVER FOR CHINA TO LEAD IN EV PRODUCTION:

China Is a Major Petroleum and LNG Importer

China is experiencing increasingly high domestic demand for petroleum and liquefied natural gas (LNG), yet the domestic upstream industry is unable to satisfy it. One of the reasons is that China's upstream sector is dominated by its national oil companies (NOCs) and private sector participation in China can only happen with contracts with the

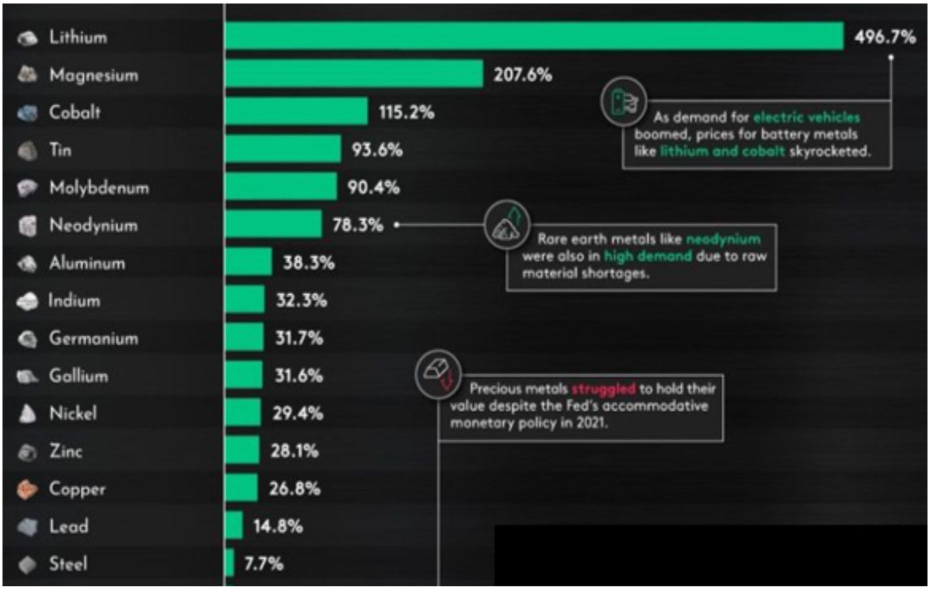


Figure 15. How Metal Prices Performed in 2021
(Source: https://elements.visualcapitalist.com/how-metals-prices-performed-in-2021/)

NOCs. Operating costs for domestic Chinese production have remained relatively high compared to the United States. Another reason limiting domestic gas production is that China's shale gas resource lies at depths greater than 3,500 meters, and available technology is not easily adapted for this depth. China will continue to import large amounts of crude and petroleum products to meet demand, as shown in Figure 16.

Additionally, because Chinese shale gas is currently inaccessible; it continues to import natural gas via pipeline and LNG terminals. Natural gas and LNG imports are both increasing due to China's continued need for more energy. China imported 54 million metric tons of LNG in 2018, a year-on-year increase of 42%. LNG imports from the US stood at 2.1 million tons, accounting for 4% of the total. Figure 17 provides an LNG import history for China.

Therefore, being short of both petroleum and natural gas, the Chinese must import and give up hard currency. By reducing fossil fuel imports, China could reduce its balance of payments, however, the type of fossil fuel imports matters greatly when the prices of energy in fossil fuels, shown as United States dollars (USD) per British thermal unit (Btu) are compared.

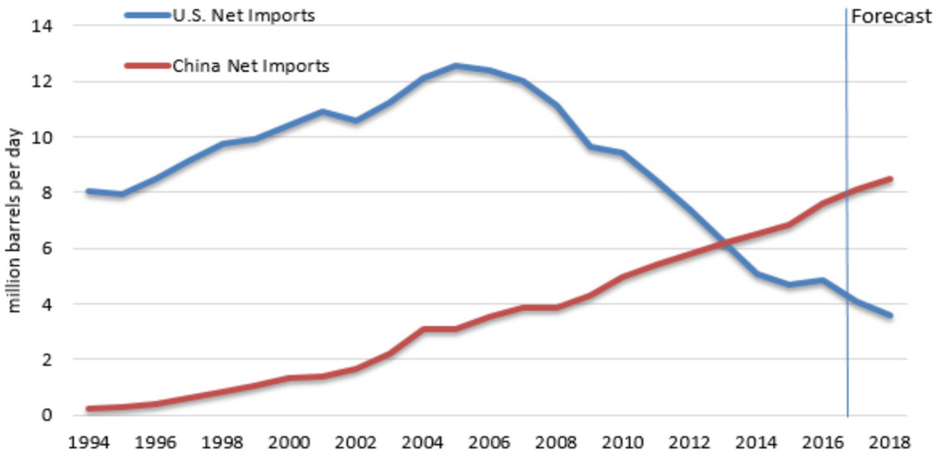


Figure 16. Net Import of Petroleum and Other Liquid Fuels Comparing China and the U.S.
(Source: Graph derived from multiple data sources within the US Energy Information Administration, April 2017)

Evaluating the imported fossil fuels China has at its disposal of coal, LNG, and crude/diesel, and spot prices in April 2022, the summary of China's fossil fuel consumption is as follows:

1. 4 billion metric tons of coal/year for electricity and steam generation, a spend of ~$1,300 billion per year with coal @ $14.57/million Btu.
2. 92 million tons of LNG each year, a spend of $90 billion per year with LNG @ $18.93/million Btu.
3. 8.6 million barrels of crude oil and refined products (diesel) per day, an expenditure of $322 billion/yr with Brent crude at $102.50/bbl.
4. Total annual fossil fuel value of $1.7 trillion.

Imported Fuel Switch Impact from Crude/Refined Products to LNG

Replacing 8.6 million barrels of crude oil/refined products per day with LNG would break even on cost between crude/refined products and LNG, but saves China ~400 million metric tons of CO_2e per year. Converting LNG to electricity for transportation energy demand is more efficient than the ICE alternative with crude/refined products/diesel for the import dollar expended. The probability for conversion of coal-fired electricity generation plants to LNG appears remote, even if the environmental prize is eliminating 9.12 billion tons of CO_2 per year.

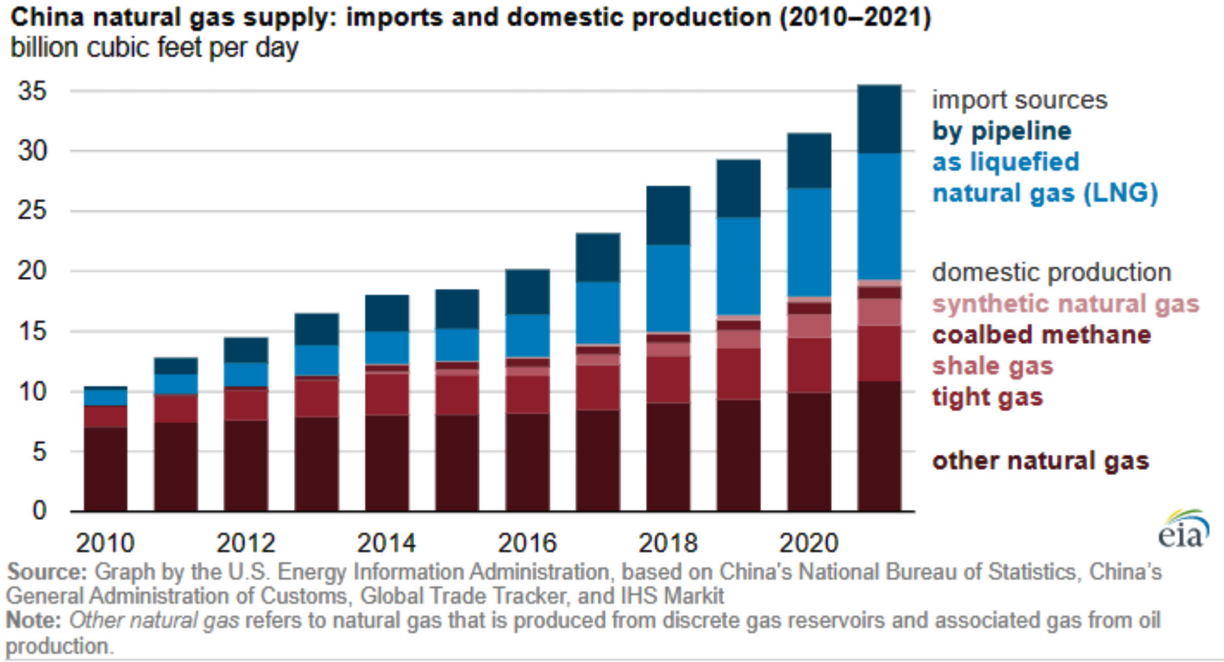


Figure 17. Chinese Natural Gas Imports by Pipeline and LNG, 2014 to 2018
(Source: EIA. Today in Energy, April 22, 2021. Available at https://www.eia.gov/todayinenergy/detail.php?id=52139. Accessed October 17, 2022.)

THE CLEAN ENERGY MINERAL CHALLENGE

The following information is reported in Daniel Yergin's book, *The New Map: Energy, Climate, and the Clash of Nations* (Penguin Press 2020):

1. ~0.5 million pounds raw materials mined/processed to make a battery for an electric car."
2. Demand for lithium up by 4,300%, cobalt and nickel by 2,500%.
3. For lithium, the top three producers control over 80%.
4. China controls 60% of rare earth output for wind turbines.
5. Democratic Republic of the Congo (DRC) controls 70% of the cobalt required for EV batteries.

SUMMARY

1. EVs will require 6 times the minerals than for ICE cars, while generating half the emissions.
2. EV mineral supply is key. New mines are needed, which mean new emissions, along with long lead times for development.
3. Supply sourcing countries may not be friendly to the West or have unstable governments.
4. Supply availability to match global demand will induce increased mineral price volatility.
5. EVs in the U.S. will double electricity generation and transmission and distribution infrastructure requirements.
6. China has huge incentives: replacing 8.6 million barrels of crude oil/refined products with LNG to save ~400 million metric tons of CO_2e per year.
7. EV mineral supply dependency will replace the current oil/gas dependency.

AUTHOR BIOGRAPHY

Ron Miller PE, CEM, REP, is an energy industry expert creating value by analyzing assets, markets, technologies, and power usage to identify, monetize, and implement profitable energy and de-carbonization projects. He is a Professional Engineer (PE), Certified Energy Manager (CEM) and Renewable Energy Professional (REP) experienced in developing and leading global energy projects in the renewable energy, conventional power, and fuels industries, before founding Reliant Energy Solutions, LLC. His global energy consultancy provides analysis for energy supply and demand, energy reliability, feasibility, fuel and energy efficiency, and de-carbonization. He has led energy project development at ExxonMobil, Xcel Energy, AECOM, Rio Tinto, and Newmont Corporation. Ron holds a BS in civil engineering from Virginia Tech and an MBA in Finance from the Terry College of Business at the University of Georgia. Ron may be reached at ron@reliantenergysolutions.com.

Implications of Variable Air Volume Flow and Occupancy Diversity on Office Building Energy Efficiency

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Fotouh Al-Ragom, PhD, CEM, CEA, CSDP, REP
Ruba Al-Foraih, CEA
Aarthi Elumalai, CEA, REP

ABSTRACT

In Kuwait, nearly 70% of overall building energy consumption is associated with the air conditioning (AC), especially in the residential sector. In a building envelope, there is heat transfer. In addition, there are multiple zones in an office building that require distinctive heat balancing that, consequently, influence the AC systems and subsystems. The manner in which the occupants occupy the various zones of the building is diverse, resulting in unusual load demand for AC and hence associated inadequacies. To evaluate the implications of variable air volume (VAV) flow in AC and occupancy diversity for an office building, the operational data for carbon dioxide sensors were analyzed and studied. The carbon dioxide concentration is one of the important indicators for analyzing the building occupancy. By knowing the occupancy in a building, not only the indoor air quality can be maintained, but also, the energy efficiency objectives corresponding to the heating, ventilating, and air conditioning (HVAC) operations can be maintained.

The correlation between the carbon dioxide (CO_2) concentration and corresponding occupancy in an office building is analyzed experimentally in this study by maintaining actual operating conditions throughout the year. Graphical trends of the CO_2 concentration and its relationship with indoor temperature were plotted, which provided information about the critical parameters affecting occupancy diversity in the selected office building. The important elements used for estimating occupancy diversity were also discussed in the paper. Therefore, the quantification of HVAC system energy efficiency influenced

by occupancy diversity can be distinguished. Even though the proposed framework is for a selected office building, this can be applied to other types of building geometries and layouts by instituting appropriate adjustments.

INTRODUCTION

Buildings account for a significant portion of overall energy consumption around the world, and Kuwait is no exception. According to Kuwait energy outlook 2019 report, residential and service sectors account for 21% of total energy consumption in Kuwait. Moreover, 70% of this energy goes to air conditioning services [1]. The hot and arid weather of Kuwait makes it necessary for people to use air conditioning systems because the temperature may rise up to 50°C during peak summer. Under such circumstances, energy efficiency enhancement to decrease energy consumption is necessary, without compromising the occupants' thermal comfort, especially in the HVAC sector. The fresh air requirements and heat gains associated with occupant load in any building are prominent factors for any HVAC system design. Therefore, the occupancy related internal heat gains, which are closely associated to dynamic organizational environment of an office building, is an important parameter [2]. The carbon dioxide emission from the occupants is contributing to the internal heat gains and fresh air requirements to a large extent.

The objective of this study is to identify how the CO_2 concentration and corresponding occupancy in an office building are correlated for better management of energy efficiency aspects pertaining to variable air volume flow in an office building HVAC system.

This article is organized in 4 sections. The first section reviews the background for modeling CO_2 concentration-related occupancy patterns. The second section describes the data collection process and methodology, which presents the method used in the study for occupancy recognition and related sensor details. The third section presents the results obtained and discusses the performances of the developed model. Finally, the fourth section summarizes the concluding remarks of this article.

BACKGROUND

Office buildings in Kuwait consume a large amount of energy to maintain thermal comfort and indoor air quality. This is highly influenced by space occupation, which is not always easy to estimate, especially in office buildings. The number of occupants in a building, the required level of indoor temperature and relative humidity for the occupants, and associated emissions, mainly carbon dioxide (CO_2), are some key parameters that influence the energy consumption of that building. Hence, the estimation of the above parameters are necessary for correctly understanding the energy consumption. At the same time, these parameters vary with time because they are all occupancy and weather dependent.

Because human behavior is stochastic in nature, the number of people or occupants in a room or a specific space for a specific duration or time is very difficult to characterize and exemplify [3, 4]. The arrival time and departure time of occupants in a particular zone is not constant. Correspondingly, the energy demand for that zone will also change, and according to that, the HVAC office management system needs to be adapted. The American Society of Heating, Refrigerating and Air-Conditioning Engineers (ASHRAE) Standard 90.1-2007, which deals with energy-efficient buildings and their design, provides suitable guidance, and explains necessary requirements for this purpose. Moreover, ASHRAE permitted the designer or modeler to determine the occupancy schedule [5, 6]. ASHRAE 90.1-2010 reintroduced the occupancy diversity factors, which are similar to ASHRAE 90.1-2004, for office buildings.

METHODOLOGY

To conduct this study, four office buildings were selected in Kuwait. The buildings have air handling units (AHUs) that are run by VAV flow. The offices in the selected buildings were either individual rooms or high/low partition rooms. The HVAC system of both buildings is controlled by building automation system that comprises control loops and zonal controls. For collecting the necessary occupancy-related data, indoor air quality (IAQ) monitors were installed in the selected buildings. The IAQ monitors are IoT (internet of technology) based ones that will continuously monitor indoor air quality at room level. It measures carbon dioxide (CO_2), PM1*, PM2.5, PM10, volatile organic compounds (VOC), formaldehyde (CH_2O), temperature, pressure, and humidity.

To monitor the IAQ, an IAQ monitor CO_2 sensor was installed. The monitor has an effective range of 400 to 5000 ppm, a resolution of 1 ppm, a maximum consistency error of ±50 ppm + 2%, a single response time of < 3 second, and a total response time of ≤ 25 second. In addition, the temperature sensors' manufacturing specifications; range from 0 to 45°C; resolution of 0.1°C; and maximum error ±0.5°C from 15° to 30°C.

The data were collected for 19 months, from March 2020 to October 2021, covering four seasons and climatic conditions. Once the data collection was completed, data validation, data sufficiency, and data variability were analyzed using statistical methods, t-test, and z-test to assure a flawless sample selection process. The energy use, lighting, and occupant thermal comfort in a room can be effectively controlled by continuously monitoring the CO_2 concentration. Human activity in the offices will increase CO_2 levels, and hence CO_2 concentration varies according to the number of occupants in each room. [This is because the metabolic activities of the employees in the office buildings impacts CO_2 levels.] The control parameter is the indoor temperature of the office buildings. The number of occupants inside the office dictates the increase or decrease in CO_2 level and, correspondingly, the ventilation requirement. The offices are usually occupied from 7:30 am to 3:00 pm on weekdays and mostly remain vacant during the weekends. Sunday to Thursday are the weekdays, with Friday and Saturday off.

Using the collected data, the trends of CO_2 concentration levels for several rooms were analyzed under various operational levels. To determine which features of the selected offices may influence the CO_2 level and to develop a correlation between them and the number of occupants present, a connection with the HVAC system was established, in which the temperature and CO_2 concentration levels were both controlled. The

*The particulate matter (PM), which is common in dust, pollen, and allergens. Extremely fine and fine particles that are less than 1 microns and 2.5 microns are referred to as PM1 and PM2.5, respectively. Inhalable particles are usually 10 microns or less and are referred to as PM10.

following section shows some distinctive findings obtained based on the study.

RESULTS AND DISCUSSION

Based on the average outside temperature measured, the hottest day where the temperature peaked at 43.5°C was July 28, 2021, and the coolest day, where the lowest temperature measured was 10.5°C was on January 24, 2021. The CO_2 concentration level and the indoor ambient temperature for these days, for office 1 were plotted on an hourly basis, and this is shown in Figures 1 and 2. From Figure 1, it is observed that the indoor ambient temperature for office 1 varies from 20.8°C at 7:00 am to 22.3°C at noon and goes down again to 21°C by 11:00 pm. It is observed from the study that the CO_2 concentration increases during the office working hours (7:30 am to 3:00 pm) reaching its highest (543.3ppm) at 10:00 am. CO_2 concentration falls to 472.23 ppm at 3:00 pm and remains fairly stable at an average of 438 ppm till 7:00 am the following day. For the coolest day (Figure 2), it is observed that the indoor ambient temperature for the same office remains around 24.8 to 25.4°C. The CO_2 concentration is observed to reach its peak at 9 am and 1 pm, i.e., 514.52 ppm and 514.35 ppm, respectively. This illustrates that CO_2 concentration increases during office working hours when building occupants are present in their workspaces.

The hourly CO_2 concentration profile for 1 week, from Sunday to Saturday, for all four offices, for the hottest week (25 to 31 July 2021) and the coolest week (24 to 30 January 2021) are shown in Figures 3 and 4, respectively. From the figures, the CO_2 concentration remains stable during the weekends, July 30 and 31 and January 29 and 30, because there are very few building occupants during the day. Additionally, the daily CO_2 profile for 1 month during the hottest month, July 2021, and the coolest month of the same year, January 2021, in terms of working hours and non-working hours for weekdays and weekends for all four offices is depicted in Figures 5 and 6. These graphs clearly display that both the hottest and coldest month CO_2 concentration is lower during non-working hours on weekdays and also remains low during the weekends when the office building is nearly vacant.

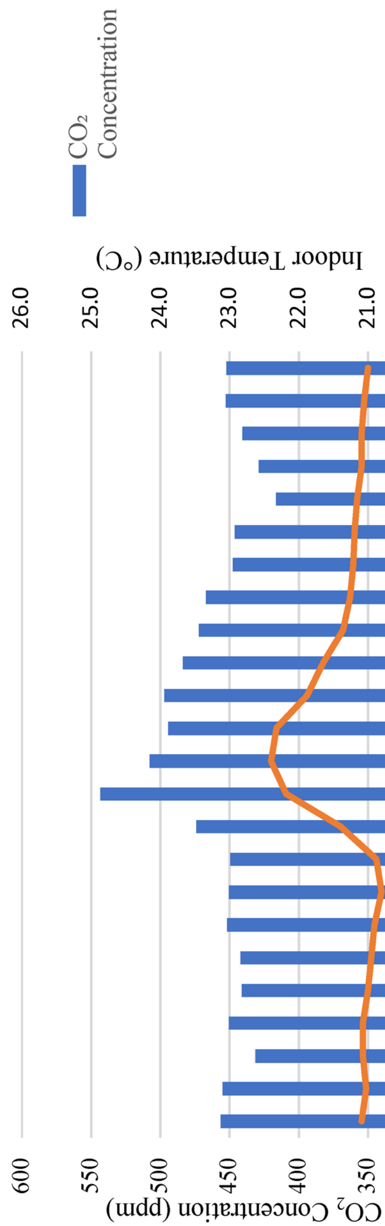

Figure 1. CO_2 and Indoor Temperature Profile for the Hottest Day

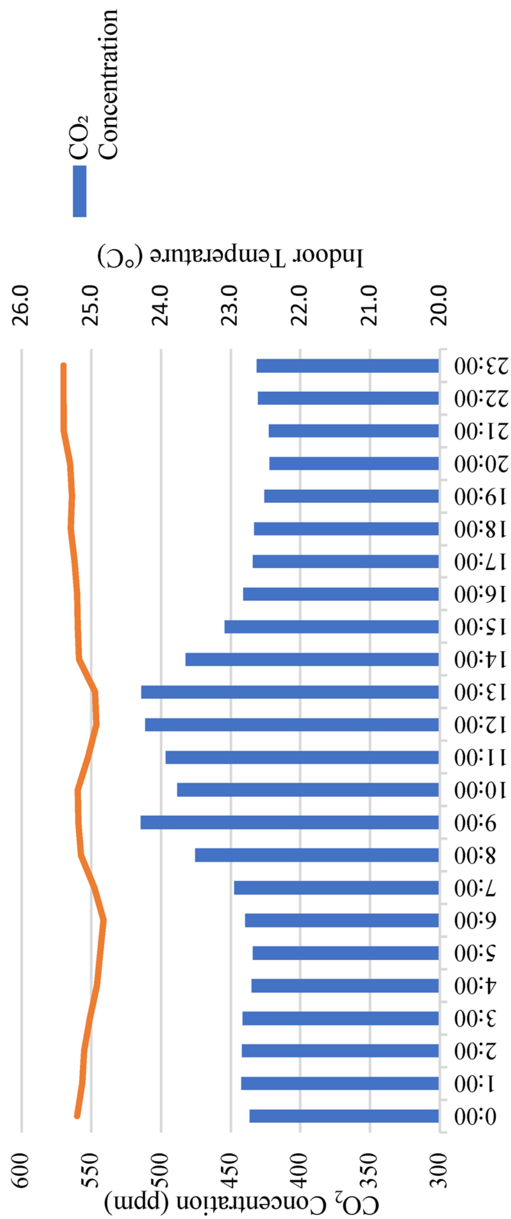

Figure 2. CO_2 and Indoor Temperature Profile for the Coolest Day

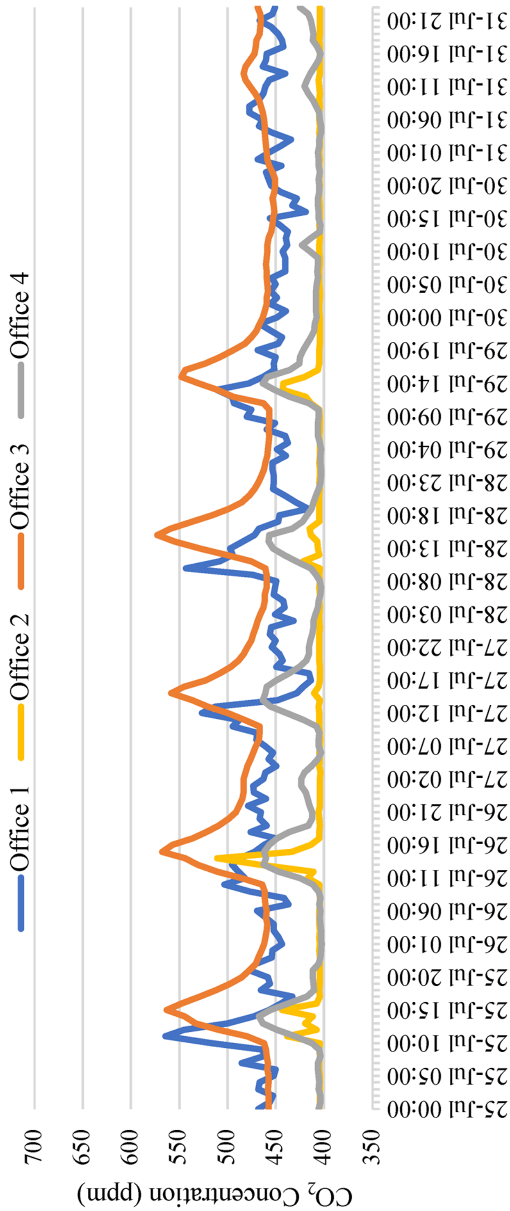

Figure 3. CO_2 Profile for the 25th to 31st July 2021

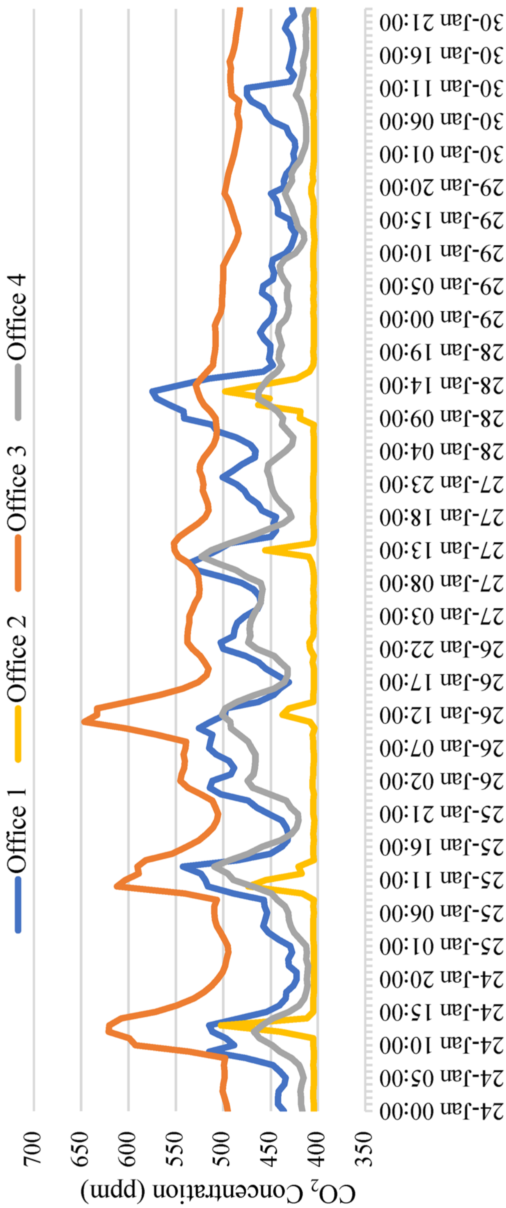

Figure 4. CO_2 Profile for the 24th to 30th January 2021

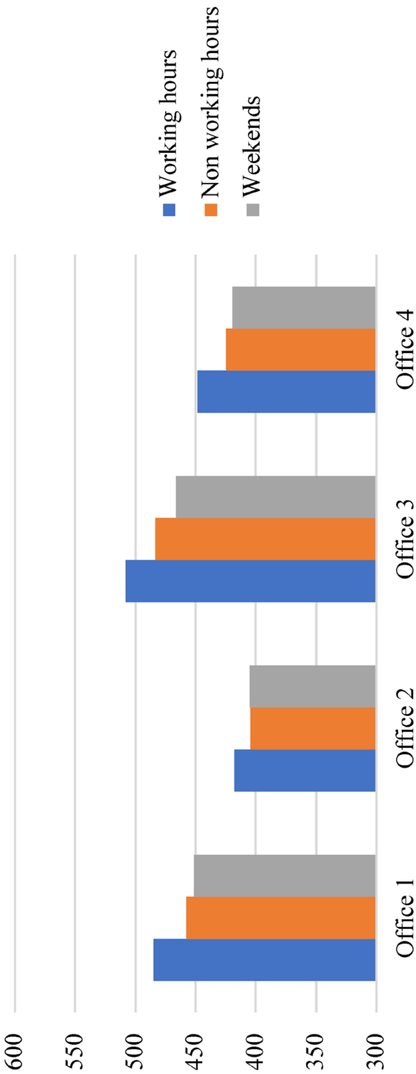

Figure 5. 30-Day CO_2 Profile for July 2021

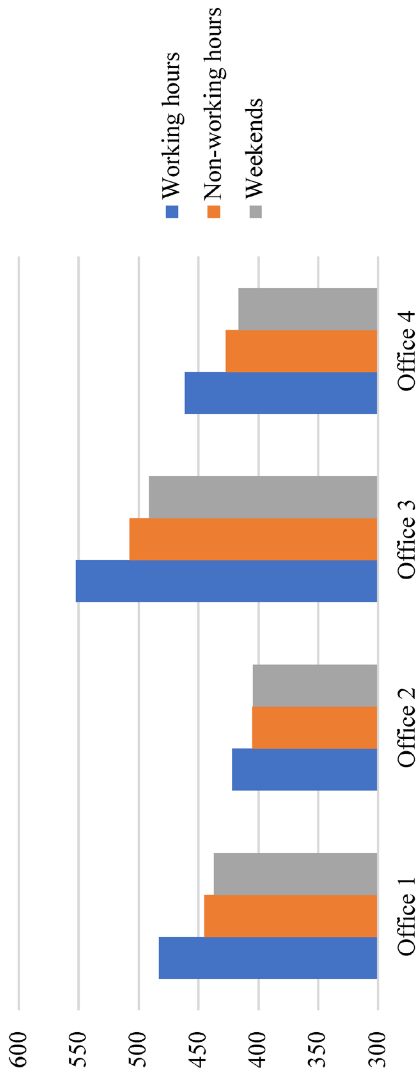

Figure 6. 30-Day CO_2 Profile for January 2021

From the daily profiles, it is observed that there is an increase in CO_2 concentration during working hours. The derivative of CO_2 concentration over time is calculated using Equation 1 for four offices [7]. Here, the difference in the CO_2 concentration at t = 8:00 am (start of the working hours) and t = 3:00 pm (end of the working hours) is calculated over the total duration of the working hours (7 hours) for each office to determine the derivative of CO_2.

$$d(CO_2)/dt = [(CO_2)(\text{at } t{=}3\text{ pm}) - (CO_2)(\text{at } t{=}8\text{ am})]/t \quad (1)$$

Table 1 presents the values for derivatives of CO_2 concentration for the hottest and coolest days. It is observed that the CO_2 derivative decreases for each office on a cool day compared to a hot day. The decrease in derivative ranges from a 35.39% decrease for office 2 to a 97.89% decrease for office 4. This change between the seasons can be attributed to changes happening in the office (i.e., controlled ventilation vs. natural ventilation).

In Figure 7, the derivative of CO_2 concentration for both the hottest and coolest days for the year 2021 are plotted against the air volume available for each occupant (V/p), where V is the total room volume and p is the number of occupants for each office. From the trend line graph, it is observed that air volume per occupant increases during the cold season; therefore, the derivative of CO_2 concentration has a higher correlation for the coolest day than for the hottest day. Also, the derivative of the CO_2 concentration (ppm/h) increases as the air volume (m3) for each occupant increases. The deviation between the seasons (summer hottest day versus winter coolest day) can be an indication of operational variances (natural versus controlled ventilation).

These results prove the importance of fresh air during winter in a thermally comfortable manner. In addition, the adherence to available thermal comfort standards such as ASHRAE Standard 55, ISO 7730 is highly essential. Real time occupancy detection is a major aspect in determining the energy efficiency strategies while considering the occupant thermal comfort, especially for a controlled indoor environment.

Table 1. Derivatives of CO_2 Concentration for the Hottest and Coolest Days

Building No.	Office No.	Total Room Volume, V (m^3)	No. of Occupants, p	Air volume for each occupant, V/p (m^3)	$d(CO_2)/dt$ for hottest day (ppm/h)	$d(CO_2)/dt$ for coolest day (ppm/h)	% decrease
Building 1	Office 1	103.68	3	34.56	3.262	1.112	65.92
	Office 2	53.31	2	26.66	1.354	0.029	97.89
Building 2	Office 3	94.93	1	94.93	16.185	10.457	35.39
	Office 4	117.94	8	14.74	7.557	0.414	94.52

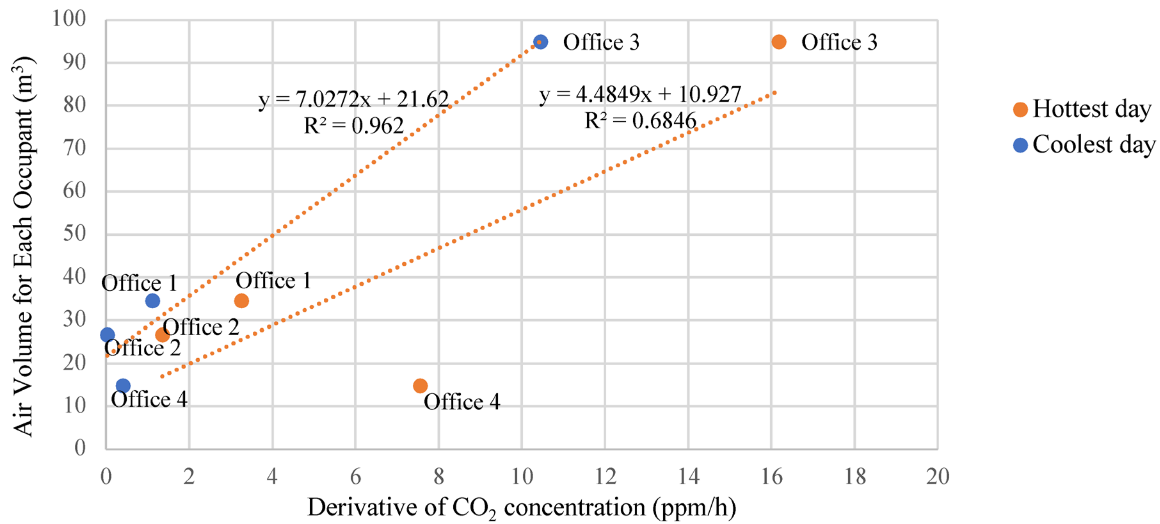

Figure 7. The Derivative of CO_2 Concentration for Both the Hottest and Coolest Days

CONCLUSION

The thermal comfort perception of occupants' is one of the important parameters to be considered while estimating the energy savings associated with buildings. Even though personal and environmental factors play a vital role in deciding the thermal comfort, there will be a considerable gap between the estimated and perceived thermal comfort sensation for occupants. A probable contender for this difference can be the increased metabolic rate and associated heat exchange with the environment, which was caused by the extra stimulation of human respiratory system. The elevated CO_2 level is a major reason for this stimulation. The outcomes of this study can help to redefine building operational strategies to optimize the fresh air supply to office buildings in arid environments. Future studies can include the estimation of CO_2 concentration and its effect on the cognitive performance of occupants, while addressing the adverse effects. This study very much emphasizes the importance of ventilation in an office building while addressing the energy conservation aspects that pave the way for micro level thermal comfort analyses in the future.

Acknowledgments

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Decarbonization Strategy for Gas Turbine Drivers in Oil and Gas Pumping Systems

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ABSTRACT

With ongoing drive and effort by companies to decarbonize their operation, there is a need to adequately monitor performance of existing assets and improve on performance. Specifically, when the focus is oil and gas companies, there are aggressive targets to decarbonize industry operations by 2040 and 2050. One of the most cost-effective enablers that supports the energy transition to achieve decarbonization target is energy efficiency. Major energy intensive sub systems/equipment includes gas turbines (GT) based drivers, electric generators, motors driven compressors and pumps, boilers, and furnaces.

It is a common practice to use GTs as drivers for pumping or compression systems in the pipeline operation areas. However, GT drivers are not the preferred option because of their lower thermal efficiency compared to other alternatives. This article will focus on evaluating different energy efficiency options for large pumping system.

Pathways considered in this article to enhance performance and decarbonization of the pumping system driven by GTs include:

- Operational load management to optimize pump station loading (short term)
- Heat to power recovery via an organic Rankin cycle (ORC) technology integration with gas turbine
- Electrification of specific assets (motor-driven pumps instead of gas turbines).

This article includes analysis on the impact of each decarbonization initiative in-terms of efficiency improvements, emissions reduction as

well as the associated net present value (NPV). In addition, the economic analysis considered different energy values for sensitivity analysis on the outcomes.

INTRODUCTION

One of the most cost-effective enablers that supports the transition to achieve decarbonization targets is energy efficiency. Major energy intensive sub systems/equipment in the oil and gas industry include gas turbines drivers (GT) and generators, motors driving compressors and pumps, boilers and furnaces, and others. A majority of oil and gas companies have aggressive targets to decarbonize operations by 2050.

Operational load management is applied to optimize pump station loading, including identifying the optimum loading of EW pump-stations via recommending a target discharge pressure for each pump-station to reduce overall system fuel consumption and CO_2 emission. An Excel-based solver along with Visual Basic for Application (VBA) programming code is used to formulate the optimization problem for the pumps' load management in a manner similar to the approach used by Tartiere and Astolfi [2].

Gas turbine exhaust provides large opportunities for waste heat recovery through heat recovery steam generation (HRSG) to provide a combined heat and power (CHP) system with system thermal efficiency over 80% [4]. Typical HRSG system require the availability of demineralized water and a large utilities system to utilize waste heat for steam generation, which require additional costs and complexity to the system. Moreover, water scarcity in some geographical regions in the world make it difficult to adopt HRSG design, and Organic Rankine cycle (ORC) offers an alternative solution for waste heat recovery from gas turbines [6].

ORC utilized different organic hydrocarbon working fluids that have lower evaporation temperatures than water and able to work with a wide range of waste heat temperatures between 95°C and 450°C [5]. There were many literature and research efforts on ORC waste heat recovery from renewable resources such as geothermal and solar thermal systems; however their application temperature was lower than 200°C, which are different with higher waste heat temperatures from gas turbines

[8]. The system operates by capturing the waste heat source through heat exchangers via closed hot oil system to evaporate and pressurize the organic working fluid to superheated conditions. This high enthalpy working fluid will in turn drive the turbo-expander or turbine to provide electric power through an electric generator [9]. The working fluid is then cooled through an air-cooled fin fan system to complete the ORC power cycle before the working fluid is heated again. Depending on waste heat temperature, system pressure and the composition of the organic working fluid, ORC system efficiency is currently lower than HRSG roughly by between 7% to 20% since more of system heat is expelled though a dry cooling system, which reduces the thermal energy efficiency [7].

This article will focus on evaluating different energy efficiency driver options for large pumping systems. However, GT drivers are not the preferred option because of their lower thermal efficiency compared to other alternatives. Pathways considered in this article to enhance performance and decarbonization of the pumping system driven by GTs include:

- Operational load management to optimize pump station loading (short term)
- Heat to power recovery via ORC integration with gas turbine
- Electrification of specific assets (motor-driven pumps instead of gas turbines)

In this article, 11 pump stations (PS) system were considered for the analysis as shown in Figure 1. Each pump station has 3 pumps connected in parallel and one or more can operate to provide required flow and pressure to meet the system requirements.

METHODOLOGY

Our methodology includes data collection, model representation of the hydraulic system (including major components performance curve and site conditions impact on the system performance), and optimization formulation. Finally, the methodology includes operating and capital cost of new modifications in the system. This is summarized in the flow chart shown in Figure 2.

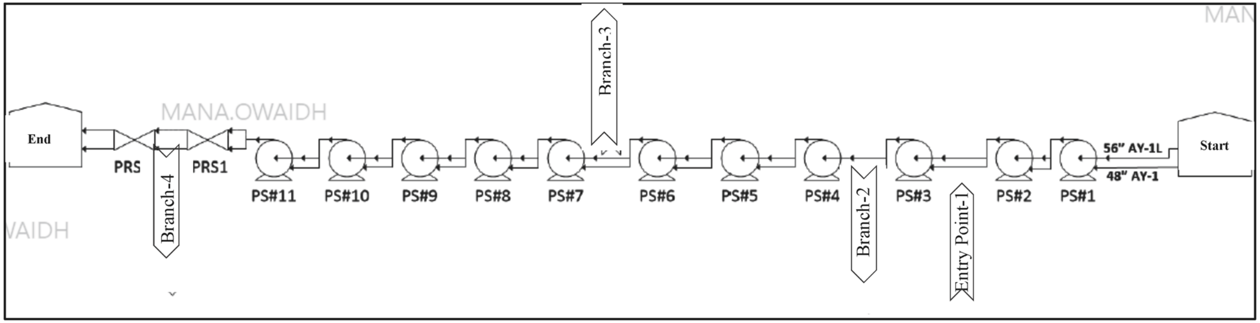

Figure 1. Pump Stations Operation

Abbreviations

PS: Pump station
PRS: Pressure reducing station
MBD: Thousand barrels per day
ORC: Organic Rankine cycle

Cases considered in the analysis

BC: Base case operation mode
P-LM: Pumps load management, optimize operation of the pumps and their drivers
ORC: Organic Rankine cycle technology, introduced to gas turbines to convert available exhaust heat from GTs into power generation.
Elect. Motor: is a new alternative for existing GTs drivers

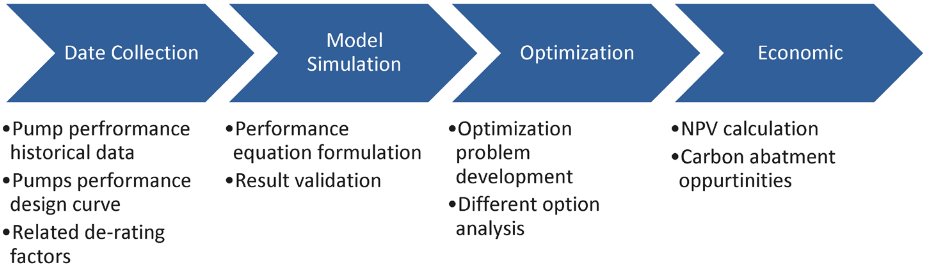

Figure 2. Methodology

PUMP STATIONS OPERATIONAL BASELINE

Arab Light (AL) crude is pumped from pump station PS#1 to PS#11 starting with 2500 thousands barrel per day (MBD) at PS#1. Table 1 includes AL crude properties used in the pumping system. On the way to PS#11, there are some branches where some crude is taken for local use. In addition, there are other entry points where some additional crude is added in the system. Table 2 provides a summary for the pump stations operational scenario considered in this article.

Table 1. Fluid Properties

Fluid Type	Crude (AL)	Units
Density	54	lbm/ft^3
Viscosity	4	cp
Atmospheric Pressure	14.7	psia
Specific Gravity	1.29	unitless

Table 2. Pump Stations Operational Scenario

Input Crude (AL)	2500	MBD
Crude from Branch 1	0	MBD
Crude to Branch 2	200	MBD
Crude to P3 through P10	2300	MBD
Crude to Branch 4	400	MBD
Total Crude to West	1900	MBD

Site ambient temperature as well as elevation will impact GT performance and production capabilities. Throughout pump stations 1-11, the elevation changes and thus the site ambient temperature changes too. Figure 3 and 4, indicate the site annual average ambient temperature and the elevation for each pump station respectively. This is an important basis used for the analysis.

SYSTEM HYDRAULIC REPRESENTATION AND MODEL FORMULATION

For each pumping system, a set of analysis, diagrams and curves have been generated. A load management model is developed for optimizing the loads on parallel plants. The analysis is applied on the complete pumping systems to calculate the optimum pressure discharge value as well as identify the optimum number of pumps that should operate in parallel.

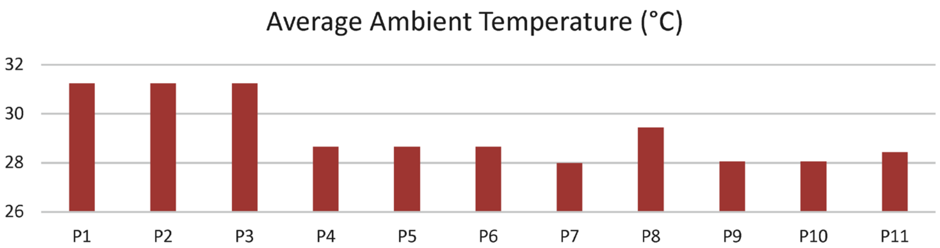

Figure 3. Average Site Condition per Pump Station

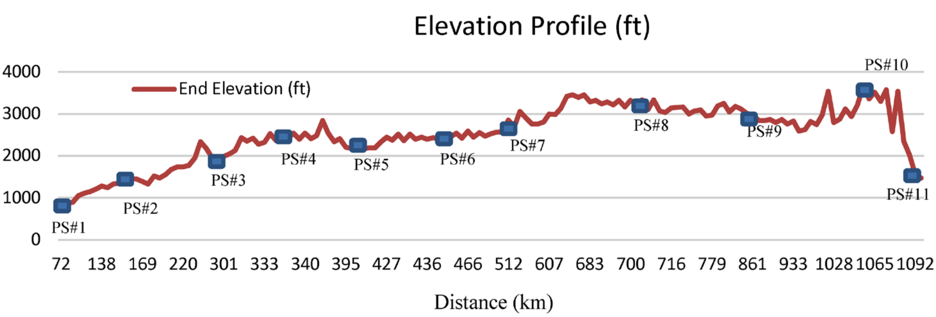

Figure 4. Elevation Profile Across the Pump Stations

In this article, a steady state hydraulic model was developed to establish the basis that represents a solid base for engineering judgment and evaluation. The hydraulic model was developed according to the following thermodynamic and fluid mechanics equations:

Equations used for the pumping system used in the formulation

Equation 1 is for calculating the velocity of the crude in the pipeline.

$$Pv = (0.286 * Q)/(24 * D^2) \qquad (1)$$

where:

Pv: Pipe velocity (ft/s)
Q: Flow (bbl/day)
D: Inside diameter (in)

$$Re = (92.24 * Q)/\{[(\mu * 62.5)/\rho] * D\} \qquad (2)$$

where:

Re: Reynolds number
Q: Flow (bbl/day)
D: Inside diameter (in)
μ: Viscosity (cp)
ρ: Density (lbm/ft³)

$$\Delta P = (0.061/1.61) * f * (Q * Re) * (\rho/62.24) * (1/(D^5)) \qquad (3)$$

where:

f: Colebrook friction factor (unitless)
Q: Flow (bbl/day)
ρ: Density in (lbm/ft³)
D: Inside diameter (in)
ΔP: Pressure drop (psi/mile)
Re: Reynolds number (unitless)

$$Pump\_BHP = Q * \Delta P/(58776 * Eff) \qquad (4)$$

where:

BHP: Pump break horsepower (hp)
Q: Flow (bbl/day)
ΔP: Delta pressure (psi)
Eff: Pump efficiency (%)

DRIVER REPRESENTATION

Gas Turbine Drivers

The rated GT power performance for ISO and site conditions are listed in Table 3. The performance curve for GT drivers was derived from operational data and machine design performance. Because these GT drivers were installed in the same period and maintained following similar operational best practices, it was assumed that these GTs have similar performance and efficiency curves. Based on historical data, a performance curve is shown in Figure 5 was generated using correlation equations (Equation 5).

$$GT\_Eff = [-0.0000000002 * (pump\_hp)^2 + 0.00001 * pump\_hp + 0.1393] * De\_rating\_F \quad (5)$$

where:

GT_Eff: Gas turbine efficiency (as indicated in Figure 5)
Q: Flow (bbl/day)
De_rating_F: De-rating factor (i.e., unitless); it takes into consideration both elevation and ambient
pump_hp: Pump horsepower required (hp)

As site ambient temperature and elevation per pump station varies, there will be some changes on GT performance and production capabilities. This is captured in a de-rated factor applied in each GT per pump station.

De-rating Factor

$$De\_rating\_F = (-0.007 * Amp\_T + 1.114) * (-0.00004 * Elev + 0.999) \quad (6)$$

where:

Amb_T: Site temperature (°C)
Elev: Elevation (ft), as indicated in Figure 4

ORC Representation

Based on a literature review on ORC design [2], as well as based on a project design of integrating a simple cycle GT unit with ORC technol-

Table 3. Gas Turbine Information

Gas Turbine	Number of Turbines per Pump Station	Rated Horsepower	Rated Horsepower	Power MW
		ISO	Site	Site
Rolls Royce RB-211	2	35000	26095	26

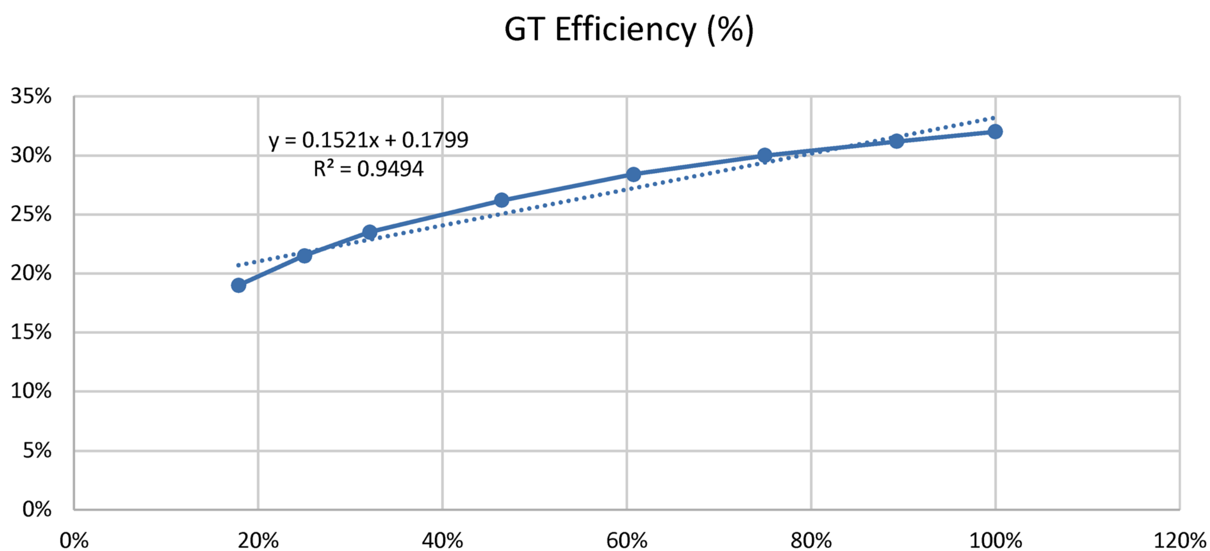

Figure 5. Gas Turbine Efficiency Curve

ogy, the maximum power recovery potential of GT rated at 21 MW at ISO condition is around 4 MW as shown in Table 4, which is equivalent to around 20% of the unit rating. This value will vary according to the load factor of GTs as well as its elevation level.

Table 4. ORC Power Recovery Rate

GT Power Output (MW) at ISO	Load	ORC Power Recovery (MW)
21	20 to 100%	1 to 4

This representation is used in the analysis related to ORC option.

Motor Driver

For simplicity, motor driver was represented by a constant efficiency curve of 94%. The electric energy required by the motor system is calculated based on the required power of the pumps. Equation 7 represents the electric power consumption of this option.

$$\begin{aligned} \text{Motor Electric Power (MW)} &= \text{(Pump\_BHP)/(Eff\_Motor)} \qquad (7) \\ &= \text{(Q * Delta\_P)/[(58776 *} \\ &\quad\ \text{Eff\_p * Eff\_m) * 0.746/1000]} \end{aligned}$$

where:

Q	Flow (bbl/day)
Delta_P	Delta pressure (psi)
Eff_p	Pump efficiency (%)
Eff_m	Motor efficiency (%)

PUMP LOAD MANAGEMENT

The objective function is to minimize energy consumption and operating cost (i.e., fuel and electric power) of all pump stations. An Excel-based solver, along with VBA code, is used to formulate the optimization problem for the pump load management in as approach similar to that used by Tartiere and Astolfi [2]. Pump optimization model consist of an objective function, decision variables and pump operational design constraints that shown in Table 5. The optimization formulation problem is listed below.

Objective Function

Total Annual Energy Cost =

$$\left(\sum_{P=1}^{11} \text{Fuel\_ps} * \text{Fuel Cost} + \text{Power\_ps} * \text{Power Cost} \right) * \text{Operating Hours} \quad (8)$$

where:

Fuel_ps: Fuel consumption per pump station

Power_ps: Power consumption per pump station

Model decision variable: The discharge pressure output for each pump station.

Subject to key constraints: Variables should be within below limits.

Table 5. Pumps Design Data

Key Constraint	Value
Maximum discharge of each pump	854 psig
Maximum BHP per pump	26,000 hp
Maximum delta pressure for each pump	764 psig
Minimum suction limit for each pump	90 psig

STUDY ANALYSIS

The analysis considered three different options for pump stations operation compared with base case operation. Each case meets the system requirements but with different energy consumption, operating and capital cost compared to base case operation. The base case represents running the system with no additional design changes and with the current operational conditions. This, predictably, results in the highest fuel gas operating costs, as well as the highest CO_2 emissions.

1. Operational load management to optimize pump station loading (short term)
2. Heat to power recovery ORC integration with gas turbine
3. Electrification of specific assets (motor-driven pumps instead of gas turbines)

Load Management (LM)

The optimum load management represents the case at which the crude is transferred from east to west at the optimum scenario. This case represents the recommended optimum operational load scenario for each pump station taking into consideration different factors such as discharge pressure and number of operating equipment. Table 6 provides energy and CO_2 emission costs used in the analysis. Table 7 provides a summary of the result of this case.

In addition, three different scenarios for energy cost were used in the analysis namely: Base, Low and High.

Table 6. Energy and CO_2 emission costs

Energy Cost	Base	Low	High	Units of Measure
Fuel	3.5	2.5	4.8	$/million Btu
Power	48	30	87	$/MWh
CO_2	20	0	100	$/ton CO_2

Figures 6 through 10 provide a summary of the different outputs of base-case operation and pump load management (P-LM) that's include PS discharge pressure, fuel consumption and BHP.

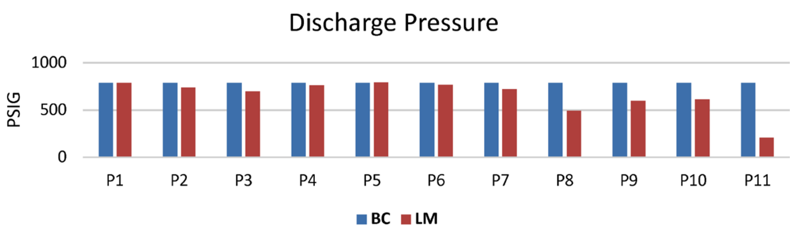

Figure 6. Discharge Pressure of Base and Optimized Load

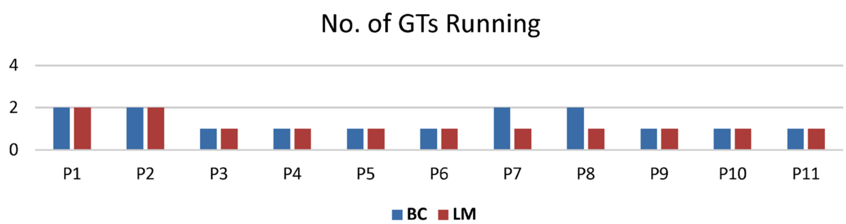

Figure 7. Running GTs Number of Base and Optimized Load

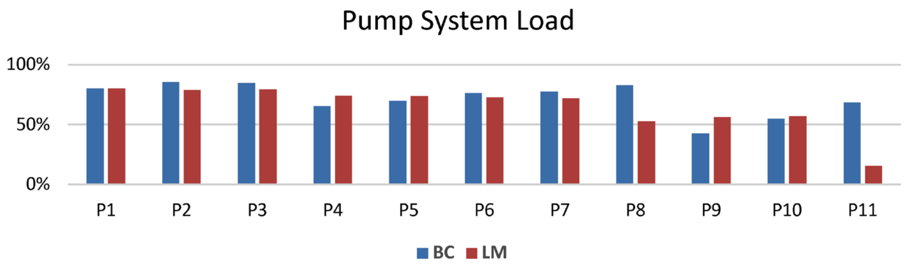

Figure 8. Pump System Load of Base and Optimized Load

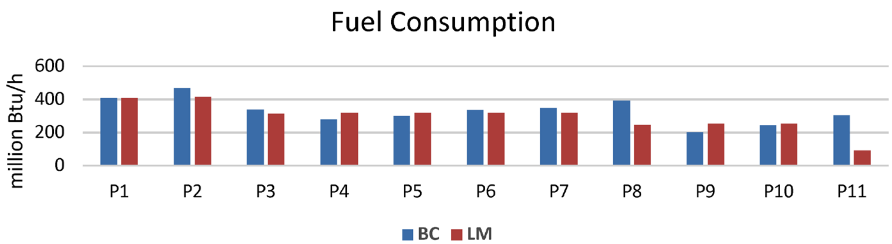

Figure 9. Fuel Consumption of Base and Optimized Load

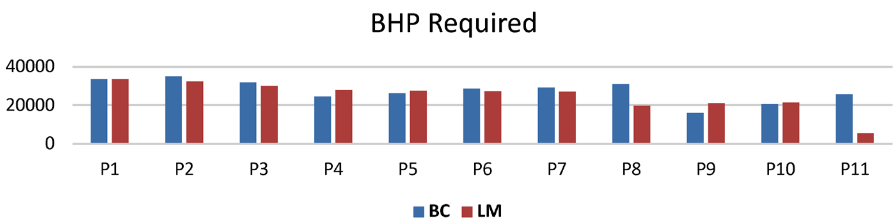

Figure 10. BHP Required of Base and Optimized Load

Table 7. Pumps Load Management Summary

Summary	BC	P-LM	Units
Total Fuel Consumption	3648	3277	million Btu/h
Total Motor Power Demand	0	0	MW
Power Recovery	0	0	MW
Net CO_2 Emissions	1.70	1.52	million ton/yr
Operating Cost (millions)	102	92	\$/yr
Capex	0	0	\$

BC: Base case operating mode

P-LM: Pumps load management, optimized operation of the pumping stations and their drivers.

ORC Integration

This case represents integrating ORC technology with GTs to recover electric power. The ORC integration will enhance the overall system efficiency. As a result, a total of 37 MW is recovered through ORC, which reduces the net CO_2 emissions for the overall pumping system. Figure 11 indicates the average power recovery for each pump station via ORC technology. This power recovery resulted from the ORC integration is at an expense of capital expenditure of around $102 million. This integration would result in $7 million operating cost savings, as well as around 120 kton/yr of CO_2 emission reduction compared to optimum load management case with no heat recovery system.

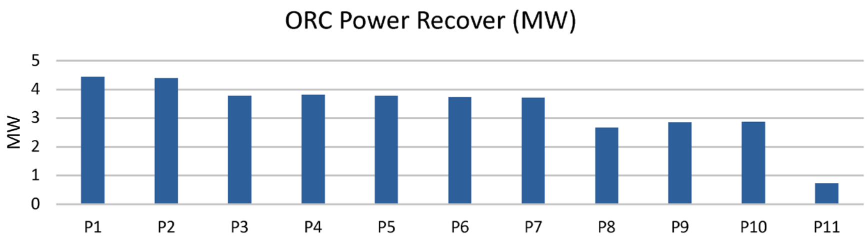

Figure 11. ORC Power Recovery

Table 8 provides a summary of the result of ORC case with incremental improvement from P-LM case.

Table 8. ORC Power Recovery Summary

Summary	BC	P-LM	ORC	Units
Total fuel consumption	3648	3277	3277	million Btu/h
Total motor power demand	0	0	0	MW
Power recovery	0	0	37	MW
Net CO_2 emissions	1.70	1.52	1.40	million ton/yr
Operating cost (millions)	102	92	85	$/yr
Capex	0	0	102	$

BC: Base case operating mode
P-LM: Pumps load management, optimized operation of the pumping stations and their drivers.
ORC: Organic Rankine cycle

Electric Motors

This option is to replace existing GTs with new and more efficient electrical motors. Because the process flow and pressure requirements are maintained, similar pumps and their related performance are kept constant in this analysis. So, the only modification in this option compared to current operation after load management is the driver efficiency and its equivalent energy requirement.

Figure 12 provides electrical energy demand for each pump station. Also, keep in mind, this result is on top of the pump load management scenario. Table 9 provides a summary of the result of electric motor case.

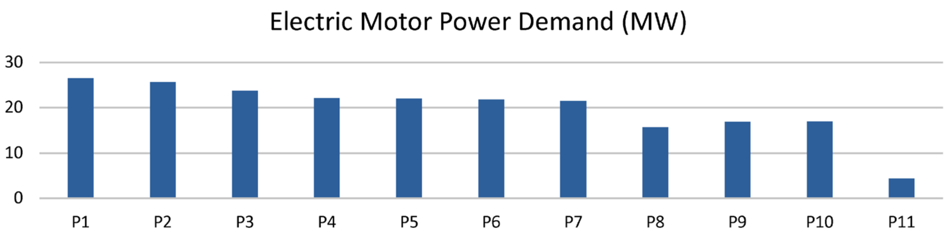

Figure 12. Electric Motor Power Demand

Table 9. Electric Motor Summary

Summary	BC	P-LM	Elect Motor	Units
Total fuel consumption	3648	3277	0	million Btu/h
Total motor power demand	0	0	218	MW
Power recovery	0	0	0	MW
Net CO_2 emissions	1.70	1.52	0.76	million ton/yr
Operating cost (millions)	102	92	38	\$/yr
Capex	0	0	73	\$

BC: Base case operating mode
P-LM: Pumps load management, optimized operation of the pumping stations and their drivers.
Elect Motor: Electric Motor

RESULTS SUMMARY

The economic analysis for each case is calculated according to net present value (NPV) as an indicator of economic feasibility. The capital cost basis for ORC and electric motors options are listed in Table 10. NPV represents the difference between the present value of cash inflows and the present value of cash outflows:

$$NPV = \sum_{t=1}^{N} \frac{R_t}{(1+i)^t} \quad (9)$$

where:

t: Time (year) of cash flow
i: Discount rate (interest rate)
R_t: Net cash flow (cash inflow – cash outflow) at time t
N: Total number of years

Table 10. Capital Cost Basis

Capex			Total Cost ($ millions)
ORC	3000	$/kW	102
Electric motor	335.1	$/kW	73

From the analysis, and as shown in Tables 11 and 12, it is clear that optimum load management of the pump station will provide high potential benefits with no cost. Thus, it's recommended to start and continue such an operational practice before and even after projects implementation. This contributes to around $10 million of energy savings with 180 kton/yr of CO_2 emission reduction compared to base-case operation.

Table 11. Electric Motor Utilizing Renewable Power Source Summary

Summary	BC	P-LM	ORC	Elect Motor	Units
Total fuel consumption	3648	3277	3277	0	million Btu/h
Total motor power demand	0	0	0	218	MW
Power recovery	0	0	37	0	MW
Net CO_2 emissions	1.70	1.52	1.40	0.76	million ton/yr
Operating cost (millions)	102	92	85	38	$/yr
Capex	0	0	102	73	$

BC: Base case operating mode
P-LM: Pumps load management, optimized operation of the pumping stations and their drivers.
ORC: Organic Rankine cycle
Elect Motor: Electric Motor

ORC integration would provide an additional cost savings of around $7 million with incremental emission reduction of 120 kton/yr compared to load management case. On the other hand, the electrification

Table 12. NPV Analysis

NPV	BC	P-LM (operational)	ORC	Electric Motor
Base	0	123	383	404
Low	0	66	259	265
High	0	279	723	772

option would provide potential savings of $54 million compared to the load management with a CO_2 emissions reduction of 760 kton/yr.

The NPV analysis is mainly used to evaluate capex related options: motor replacement case (electrification) and ORC integration. The NPV results show that electrification case is around 5% better than ORC integration case. In addition, the potential CO_2 emission reduction from the electrification case is far better than ORC integration case with almost 45%. Furthermore, in the future, we expect electrification related emissions will be significantly lower due to the high penetration of renewable energy to the electric grid.

CONCLUSION

Achieving aggressive decarbonization targets set by companies in the oil and gas industry requires reevaluation of current operations to achieve higher efficiency. This article examines alternative cases for large pumping systems including operational load management, ORC integration, and motor electrification. These three cases are evaluated from multiple dimensions including emissions and economics.

Operational load management provides significant reduction in CO_2 emissions and operating cost without additional investments. ORC integration further reduces the CO_2 emissions while reducing operational costs as well. For motor electrification, the NPV analysis shows a 5% higher NPV compared to ORC integration while delivering substantially higher CO_2 abatement by 45%.

The CO_2 abatement could reach complete decarbonization based on renewable energy penetration to the electric grid. Thus, electric motors, as an alternative to GTs, are recommended to be considered for any project design due to the associated economic and environmental advantages.

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