# The California Energy Commission's New Regulations for Computers

*A model for streamlining compliance, and an evaluation of the efficacy of California's new regulations.*

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## The Energy Problem and its Consequences

The California Energy Commission (**CEC**) is the agency tasked with planning energy usage statewide. On December 9, 2020, the **CEC** expanded its regulations on appliances to include computers. This regulation expansion intends to curtail power consumption of PCs, and more specifically gaming PCs. Per the State's own Energy Research and Development:

> *Systems used for computer gaming in California consumed 4.1 terawatt-hours/year in 2016 or $700 million in energy bills, with emissions of 1.5 million tons carbon dioxide*

This places computer gaming at one-fifth of all miscellaneous household power consumption statewide. Surely, this expansion of regulations for such a power-hungry appliance was inevitable.

After December 9, 2021, if a submitted PC does not conform to the new regulations, it cannot legally be bought or sold in California, which is home to virtually all top gaming computer manufacturers, including: iBuyPower, NZXT, CyberPowerPC, and Skytech Gaming (the company I currently work for).

Among many minute details, there are three main consequences for computer manufacturers under these regulations:

### 1. High Expandability

PCs must now consume below a threshold of power consumption (in watts). This threshold is largely determined by the expandability score of a PC's motherboard. The specifics are a bit complicated, so simply put, the CEC wants manufacturers to build with high-expandability motherboards, which are typically higher-end motherboards. The more expandable a motherboard is–i.e., the more a motherboard allows for additional graphics card(s), storage, memory, or USB peripherals–the more energy a PC is allowed to consume. This is perhaps the most controversial for consumers and tech bloggers, as higher-end motherboards not only add a more prohibitive cost, but many suspect that these higher-end motherboards also consume more power. An article written by ReasonTV exemplifies much of the handwringing over this detail of the new regulations:

> *There is a certain logic to this: More powerful computers typically need more electricity to operate. But since the smaller, simpler computers hit their energy consumption limits more easily than expanded computers do,* ***the rules are actually encouraging people to get bigger computers that consume more electricity.***

Although I will not be referencing the details of the formula directly, I will later analyze how High-Expandability Score (**HES**) affects power consumption. So, here's formula if you're interested in understanding how HES is calculated:

$$
\begin{aligned}
&Expandability\ Score \\
&\quad = 100 + 5 \times Number\ of\ USB\ 2.0\ Ports \\
&\quad + 10 \times Number\ of\ USB\ 3.0\ or\ 3.1\ Ports\ (Gen\ 1) \\
&\quad + 15 \times Number\ of\ USB\ 3.0\ or\ 3.1\ Ports\ (Gen\ 2) \\
&\quad + 100 \times (Number\ of\ \geq 100W\ USB\ or\ Thunderbolt\ \ Port) \\
&\quad + 60 \times (Number\ of\ \geq 100W\ USB\ or\ Thunderbolt\ \ Port) \\
&\quad + 30 \times (Number\ of\ \geq 100W\ USB\ or\ Thunderbolt\ \ Port) \\
&\quad + 10 \times (\text{Unconnected USB 2.0 Header?}) \\
&\quad + 20 \times (Unconnected\ USB\ 3.0\ or\ 3.1\ Header?) \\
&\quad + 25 \times (Number\ of\ 1x\ or\ 4x\ PCIE\ Slots) \\
&\quad + 75 \times (Number\ of\ 16x\ PCIE\ Slots) \\
&\quad + 20 \times (Number\ of\ Thunderbolt \geq 2.0\ ports) \\
&\quad + 10 \times (Number\ of\ M.2\ (not\ key)\ slots) \\
&\quad + 15 \times (Number\ of\ IDE\ or\ Sata\ or\ ESATA\ ports) \\
&\quad + 25 \times (Number\ of\ M.2\ keys\ or\ SATA\ Express\ ports\ or\ U2\ ports) \\
&\quad + 50 \times (Integrated\ Liquid\ Cooling?) \\
&\quad + 100 \times (Support\ for\ 4 + channels\ of\ RAM)
\end{aligned}
$$

For what it's worth, Energy Star (the US Government's energy efficiency program) has done research on the CEC's HES and determined that it is nonsensically complex. With *just two* of the metrics in the CEC's formula (number of PCIE slots and number of USB 3.1/Thunderbolt ports), you can successfully categorize PCs by energy consumption just as well as the CEC's model. Please California, learn about the merits of parsimonious models!

## 2. 80 Plus Gold Certified Power supplies

This requirement is straightforward: all PCs bought and sold in California must have an 80 Plus rating of “Gold” or higher (the tiering is Titanium>Platinum>Gold>Silver>Bronze>White). Again, another cost added for consumers. Previously, Bronze and White rated power supplies were common in lower-end gaming PCs.

## 3. All PC models bought and sold in California must be tested and submitted to the CEC

This requirement is by far the most troublesome for manufacturers. The level of detail the CEC requires means that *every* combination of components must now be a unique PC model. Prior to the regulations, companies like the one I work for would sell a PC and list the motherboard and power supply specifications like so:

- Motherboard: B550 chipset
- Power Supply: 650-Watt Gold

Manufacturers did not have to specify *which* power supply or motherboard was being used for that particular model, as supplies for these components are volatile and motherboards/power supplies of similar specs are largely interchangeable. Now, the CEC wants all such combinations to be brand/model specific for motherboards and power supplies, and then submitted to the CEC under a unique PC model name.

Now that the important details of the CEC’s regulations are covered, let’s discuss the problems created by them.

## Problem 1: Efficacy

With these regulations add problems for both manufacturers and consumers alike, it begs the question: ***Are the regulations effective?*** I will attempt to answer this by exploring the available data to see if high-expandability and Gold power supply requirements truly result in lower power consumption. If they are not effective, how so? How can these regulations be improved?

## Problem 2: Labor

The requirement to test and submit every combination of components respective of brand and model creates a massive, unrealistic labor problem for manufacturers. From my own company's standing inventory, we have **27** unique motherboards, **15** unique Gold Power supplies, **20** unique graphics cards (not brand specific, e.g., an NVIDIA ASUS 3080 is the same as a NVIDIA Gigabyte 3080), and **26** unique CPUs. Via the product rule, that amounts to **210,600 unique combinations** for components, and roughly 157,950 hours of testing. Realistically, manufacturers would not actually combine all available components (for example, a high-end GPU and a low-end CPU don't really make sense to pair). Still, the labor cost is prohibitive – one that could potentially monopolize the market as only established brands could shoulder the time and cost.

To address this issue, I will build a model that can predict power consumption using data related to the components. I see four potential use cases for this:

1. Eliminate combinations that would not pass CEC testing.

2. The CEC could use a similar model to detect outliers that are submitted to them: does the reported power consumption seem unlikely given the model's predicted power consumption? This could be useful for enforcement, as many companies are already looking for ways around the problem (i.e., models like the one I will make).

3. While neither I nor my company condone fraudulent testing, a predictive model like this *could* be used as a replacement for testing altogether, once sufficient data has been collected to form a base. There are severe ethical and legal concerns with this application, though it is possible.

4. Most importantly, building a successful model could aid in evaluating the attributes required in data submissions to the CEC. This aids in answering the concern of efficacy and providing feedback on how the CEC can improve their regulations.

## The Data

| CPU Cores | Core Speed (GHz) | Number of hard disk drives | Number of extra solid-state drives | GPU Bandwidth | Ram Speed (GB/s) | RAM Capacity (GB) | Motherboard | PSU | PSU Size (Watts) | Short-Idle Power (Watts) |
|---|---|---|---|---|---|---|---|---|---|---|
| 8.0 | 3.5 | 0.0 | 1.0 | 512.0 | 28.8 | 16.0 | MSI Z590 GAMING EDGE WIFI | 220-G5-0850-X | 850.0 | 52.69 |
| 8.0 | 3.5 | 0.0 | 1.0 | 512.0 | 28.8 | 16.0 | MSI Z590 PRO WIFI | 220-G5-0850-X | 850.0 | 49.13 |
| 10.0 | 3.7 | 0.0 | 1.0 | 512.0 | 28.8 | 16.0 | ASROCK Z490 TAICHI (WI-FI) | XPG CORE REACTOR | 650.0 | 46.80 |

To address these two issues, I will use data directly from the CEC's public database: MAEDbS.

The raw data contains over 8000 submissions, but it should be noted that a lot of them are *duplicates* under different PC model names. After removing the PC model name and filtering duplicates, we are left with 1,672 unique submissions/rows from 16 different computer manufacturers. To be clear, each row is a specific computer model and its accompanying components and their features.

The data consists of several attributes, of which I used 11 (not including outcome variable). *Many* of the columns in the raw data are completely irrelevant to power consumption or merely descriptors of the PC.

## Attributes

Here is a brief description of the attributes we will focus on:

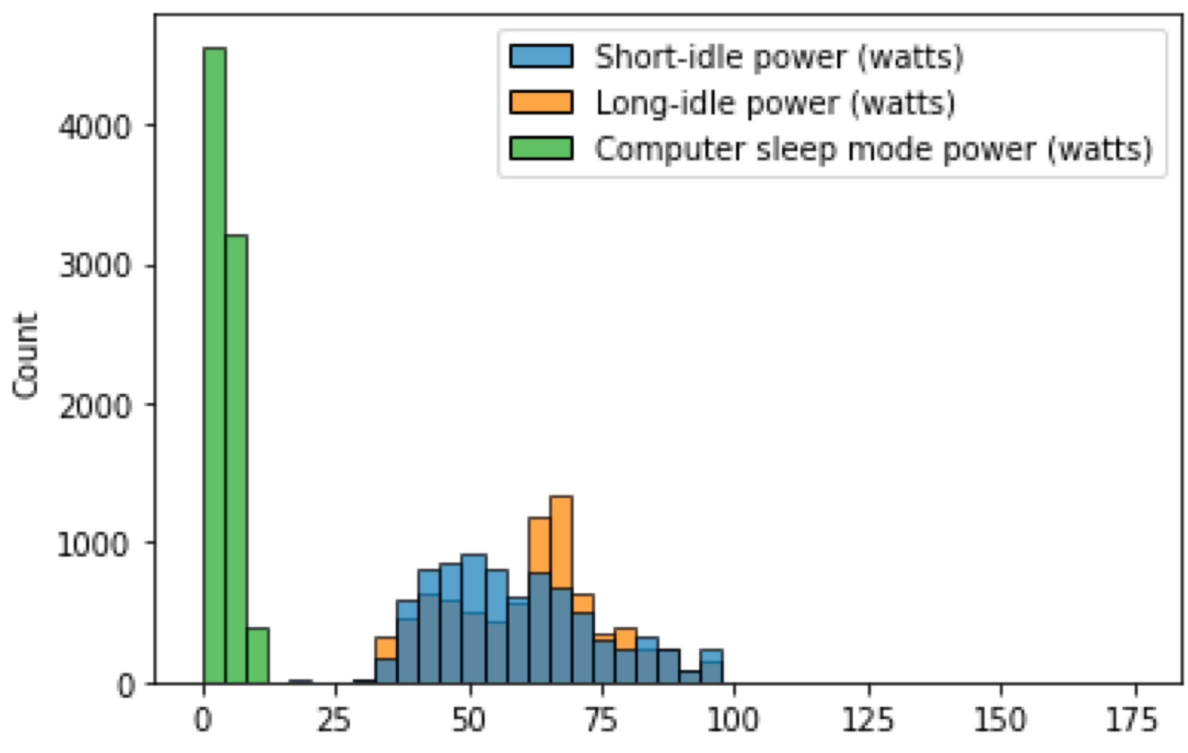
1. CPU Cores: the number of cores a CPU has. While not the only descriptor of the capabilities of the CPU, higher core count is usually an indicator of high-end CPUs.
2. Core Speed (GHz): This is the base speed of the CPU. CPUs often oscillate above and below this value, based on the load it is handling.
3. Number of hard disk drives
4. Number of *extra* solid-state drives: this is the number of additional solid-state drives used for storage, not including the primary drive that holds the operating system.
5. GPU Bandwidth: a measure in gigabytes per second of the data transfer speed of the graphics card to the interface it is connected to (in all of these cases, that is the PCIE slot on the motherboard).
6. RAM Speed: a measure in gigabytes per second of the clock speeds of the memory sticks in the PC.
7. RAM Capacity: a single RAM module's capacity in gigabytes.

8. Motherboard: this needs to be the individual motherboard model. Ideally, manufacturers would provide the brand and accompanying manufacturer part number, but there is no enforcement on clean data here so different manufacturers don't include all that is necessary to identify a motherboard. This is by far the messiest of the dataset.
9. PSU: same requirements as the motherboard, but for the power supply (PSU).
10. PSU Size: a measure in watts of the maximum power it is capable of using.
11. High Expandability Score: calculated from the formula above. A score of 690 or above indicates that the motherboard can be classified as sufficiently high-expandable, and thus allowed a much higher threshold of power consumption.

### Outcome Variable

Finally, we have our outcome variable: Short-Idle Power. Short-Idle Power is a measure in watts of how much energy the PC is consuming within a 15-minute interval of being idle on the desktop, with the computer's display on.

| | Short-idle power (watts) | Long-idle power (watts) | Computer sleep mode power (watts) |
|---|---|---|---|
| **mean** | 58.958719 | 60.870154 | 4.266051 |
| **std** | 15.260163 | 14.972945 | 2.086310 |



The data submitted to the CEC actually requires 3 measures: short-idle, long-idle, and sleep mode power. I opted to not use long nor sleep mode power for the model to explain, as long-idle differs very little from short-idle power in terms of distribution, mean, and variance. Sleep idle also follows a much tighter distribution and doesn't vary much between PCs.

## Data Preparation

I handled data preparation differently in addressing efficacy than I did for the model to address the labor problem. The reason for this is because the full dataset contains data for *many* computer manufacturers. However, I don't particularly want to do a lot of the legwork for our competition, so in the model I focused entirely on data that my own company has submitted (Skytech Gaming)

## Data Cleaning for Problem 1

Data preparation for the entire dataset was fairly minimal for the first problem.

```
df['HES'] = df['Expandability Score'].apply(lambda x: True if x >= 690 else False)
```

In order to answer the question of whether the *expandability* of a motherboard matters for power consumption, I transformed the high-expandability score from a continuous to Boolean value in order to compare the power consumption of both high-expandable and non-high expandable motherboards. Again, the threshold for high-expandibility is 690. If PCs contain motherboards that meet this threshold, they are afforded more watts as the upper limit in an idle state.

```
print(f"Mean for Bronze PSU: {round(np.mean(df[(df['PSU'] == 'GP-P650B') & \
                         (df['CPU'] == (16.0, 3.4))]['Short-Idle Power (Watts)']), 2)}")
print(f"Mean for Gold PSU: {round(np.mean(df[~(df['PSU'] == 'GP-P650B') & \
                         (df['CPU'] == (16.0, 3.4)) & (df['PSU Size (Watts)'] == 650) & \
                         (df['GPU Bandwidth'] == 512.0)]['Short-Idle Power (Watts)']),2)}")
```

I didn't plan on being able to address the Gold power supply problem at first, but to my surprise, some manufacturers uploaded data using Bronze power supplies. This is not allowed by the CEC, but we will take advantage of this mistake to compare power consumption of Bronze and Gold power supplies. The model for the Bronze power supply is the GP-P650B, which was submitted in PC models using a 16 core, 3.4 GHz CPU and a 512 bandwidth GPU. I then filtered the dataset to *exclude* this model of power supply, while holding the CPU, GPU, and wattage (650) the same to compare it against Gold power supplies.

## Data Cleaning for Modeling

Admittedly, my company's data was not clean at all. The biggest issue I saw is that we did not normalize our naming for motherboards, so models like the ASRock B550 Taichi were sometimes logged as just *B550 Taichi* or *ASRock Taichi*.

```python
def mobo_to_chipset(x):
    chipsets = ('B550', 'B560', 'X570', 'Z590')
    if 'B550' in x:
        return('B550')
    elif 'B560' in x:
        return('B560')
    elif 'X570' in x:
        return('X570')
    elif 'Z590' in x:
        return('Z590')
    else:
        return('Unknown')
```

```python
skytech['Chipset'] = skytech.Motherboard.apply(lambda x: mobo_to_chipset(x))
skytech.drop(columns = ['PSU', 'Motherboard'], inplace = True)
```

While it might seem like a copout solution, I opted to transform the motherboard column to simply encode the *chipset* of that motherboard model. In other words, an ASRock B550 Taichi turned into a "B550", which would be the same as an ASUS Prime B550. I have 3 reasons for this:

1. The actual features of the motherboard are already encoding in the *Expandability Score* column, thus making it redundant to add the name.
2. There was a severe class imbalance between some models
3. Avoiding *the curse of dimensionality*. One-hot encoding for chipset rather than individual models would result in a much more manageable level of sparseness. With dozens of unique motherboard models, one-hot encoding for each would result in a terribly sparse dataset.

Similar logic applies to dropping the power supply models: dimensionality/representation concerns, and the primary predictive value is already encoded in the PSU's Size (in watts).

```
skytech.Chipset.value_counts()
```

```
B550    83
X570    35
B560    32
Z590     7
Name: Chipset, dtype: int64
```

Still, after transforming motherboard to chipset, there was some class imbalance – a much more manageable level that I opted to do some Random Oversampling.

After cleaning, the data fed into the model looked like this:

| CPU Cores | Core Speed (GHz) | Expandability Score | Number of hard disk drives | Number of extra solid-state drives | GPU Bandwidth | Ram Speed (GB/s) | RAM Capacity (GB) | PSU Size (Watts) | Chipset_B550 | Chipset_B560 | Chipset_X570 | Chipset_Z590 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 8.0 | 3.6 | 510.0 | 0.0 | 0.0 | 912.0 | 25.6 | 16.0 | 750.0 | 1 | 0 | 0 | 0 |
| 8.0 | 3.6 | 610.0 | 0.0 | 0.0 | 608.0 | 28.8 | 16.0 | 750.0 | 0 | 0 | 0 | 1 |
| 8.0 | 3.8 | 730.0 | 0.0 | 0.0 | 608.0 | 25.6 | 32.0 | 750.0 | 0 | 0 | 1 | 0 |
| 8.0 | 3.8 | 730.0 | 0.0 | 0.0 | 608.0 | 25.6 | 16.0 | 750.0 | 0 | 0 | 1 | 0 |
| 12.0 | 3.7 | 730.0 | 0.0 | 0.0 | 608.0 | 28.8 | 32.0 | 850.0 | 0 | 0 | 1 | 0 |
| ... | ... | ... | ... | ... | ... | ... | ... | ... | ... | ... | ... | ... |
| 8.0 | 3.8 | 580.0 | 0.0 | 0.0 | 608.0 | 25.6 | 32.0 | 750.0 | 0 | 0 | 0 | 1 |
| 8.0 | 3.8 | 580.0 | 0.0 | 0.0 | 608.0 | 25.6 | 32.0 | 750.0 | 0 | 0 | 0 | 1 |
| 8.0 | 3.6 | 585.0 | 0.0 | 0.0 | 912.0 | 25.6 | 32.0 | 850.0 | 0 | 0 | 0 | 1 |
| 8.0 | 3.6 | 585.0 | 0.0 | 0.0 | 912.0 | 28.8 | 32.0 | 850.0 | 0 | 0 | 0 | 1 |
| 8.0 | 3.6 | 610.0 | 0.0 | 0.0 | 608.0 | 28.8 | 16.0 | 750.0 | 0 | 0 | 0 | 1 |

I also used a Min-Max Scaler over others, as these aren't exactly continuous variables despite being floating point values: they are counts of a discrete nature (e.g., RAM only really takes values of 8, 16, and 32 GB).

Finally, the data was split into an 80/20 train-test split after some trial and error to prevent over/underfitting.

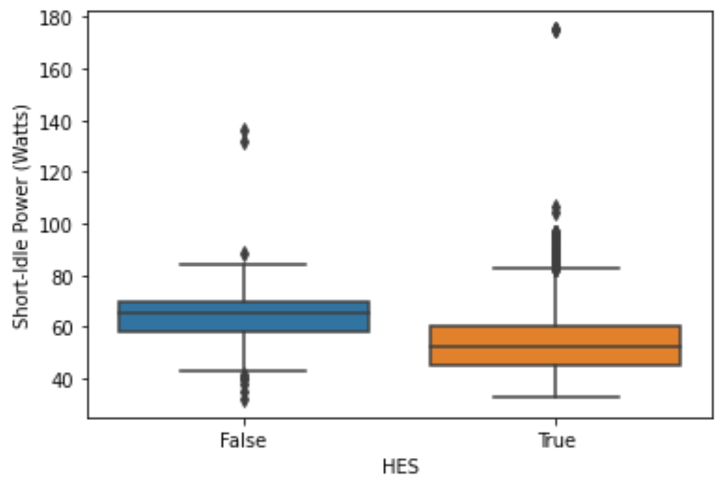
## Addressing Efficacy of High-Expandability

While this step was simple, it was the most unexpected result for me. As I mentioned in the description of the problem, much handwringing has been done over this push for high-expandability.

Many, including myself, considered this requirement bizarre with the following logic: High-Expandability = more motherboard features = higher-end motherboards = more power consumption. Would the CEC really achieve the *opposite* of their goal and cause people to buy more power-hungry machines?

While these motherboards *are* capable of housing more GPUs than non-high-expandability motherboards, with a single GPU they turned out to be *significantly* less power hungry than lower-end, non-high-expandability motherboards.

| HES | mean | std |
|---|---|---|
| False | 64.287917 | 14.781234 |
| True | 54.427978 | 13.394013 |




Numerically, visually, and statistically, the high expandable group consumed *significantly* less power: nearly 10 whole watts worth! A t-test produced a p-value of 3.93607709619168e-12, which allows us to reject the null that the difference in these group means is zero.

Why might this be? Without knowing the details of the architecture of more modern interfaces like USB 3.0 and Thunderbolt, I would assume they are simply more power efficient than older interfaces like USB 2.0. So, it turns out the opposite of the gaming community's common sentiment turned out to be true: **high expandability is a good thing.**

Still, the scoring methodology is very flawed. As I mentioned earlier, per Energy Star's research, Total Annual Energy Consumption can be explained just as well with just *two* of the elements of the CEC's expandability score formula. High expandability? **Good**. The CEC's metric of it? **No.** Reducing the number of attributes to measure, as well as removing the motherboard model requirement would both *drastically* reduce the labor problem of testing all motherboards used.

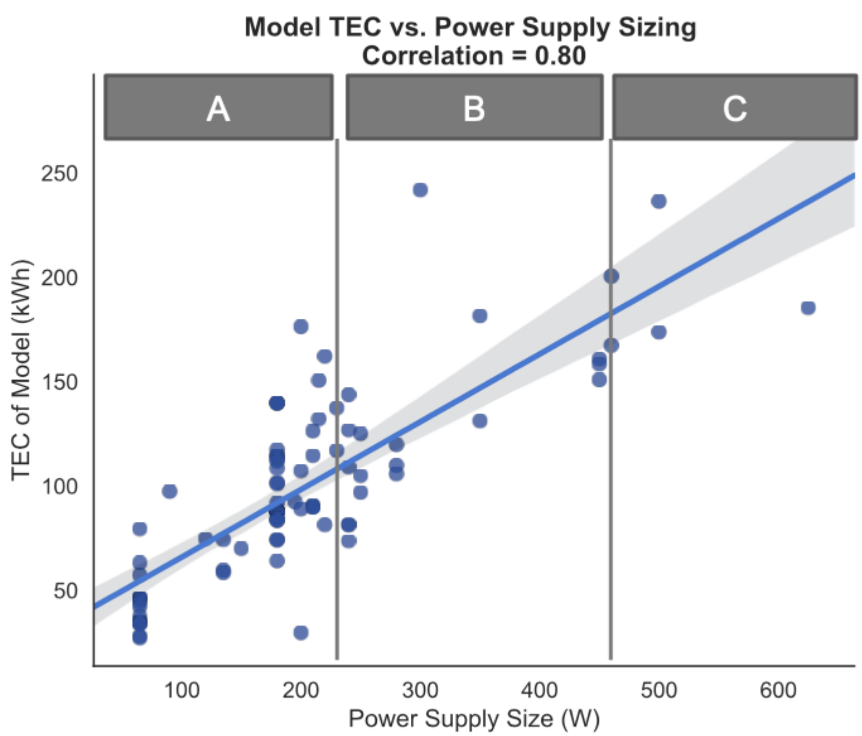
### Addressing Efficacy of Gold Power Supplies

Testing this was simple: the means between Bronze and Gold power supplies in a Short-Idle state are ***not significantly different***. With a t-test p-value of .42, we cannot reject the null that their difference is zero. The Bronze power supplies had a mean of 49.57, and Gold 50.86.

It's important to note that power supply efficiency is largely an issue at low-power states. This must be why the CEC is primarily concerned with measurements at an idle state, as under load, their efficiencies are negligible. Given these results, however, the differences really aren't much different at a low-power state.

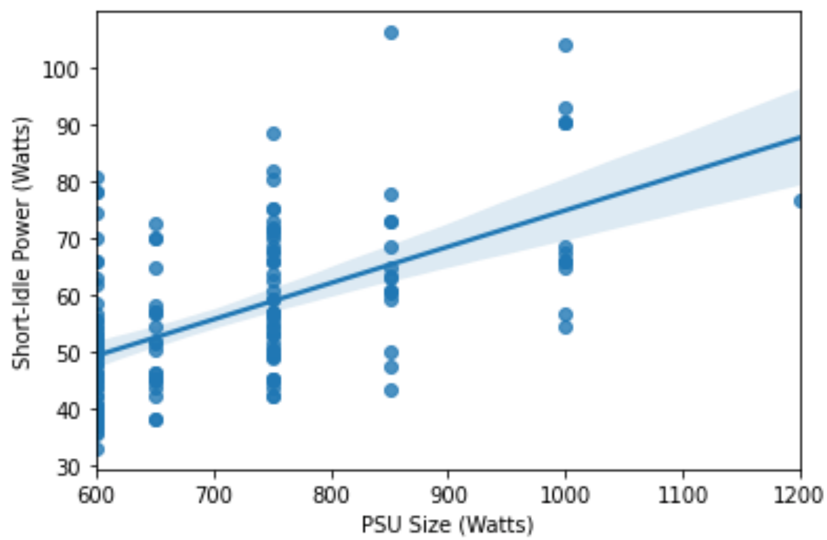
So, requiring Gold rated or higher power supplies is nonsensical in my view. It adds a barrier of entry into PC gaming that is unwarranted by the minimal effects it has on power consumption, if any.

Additionally, I'd take this a step further and claim that reporting any power supply information beyond the max capacity wattage is a waste of labor and an unwarranted regulation. 80 Plus Rating has long been criticized by PC enthusiasts, and rightfully so: it's often used to market more expensive power supplies without much benefit. It turns out that EnergyStar.gov agrees!




The above figure is from their own research on Total Annual Energy Consumption (TEC) in response to the CEC's regulations. It turns out that wattage is a very strong indicator of TEC, so why the need to encode more data that both inhibits affordability, and creates unnecessary testing and labor for manufacturers? My own data echoed their sentiments, with a virtually similar relationship between power consumption (Short Idle in my case) and wattage:

Pearson's Correlation Coeff: 0.5608739139384483




## Model Selection and Results

I opted for a Random Forest Regressor and a Gradient Boosting Regressor simply because I had already done some preliminary research for my job on this topic to see what affects power consumption most, and these two algorithms performed the best then.

## Random Forest Regressor

```
rfr_grid = {
    'bootstrap': [True],
    'max_depth': [80, 90, 100, 110],
    'max_features': [2, 3],
    'min_samples_leaf': [3, 4, 5],
    'min_samples_split': [8, 10, 12],
    'n_estimators': [100, 200, 300, 1000]
}
search_rfr = GridSearchCV(rfr, param_grid = rfr_grid, cv = 3)
```

Using the above cross-validated grid search, I managed to achieve the following results:

```
Tuned Random Forest Results
---------------------------
Training R^2 Score: 0.82
Testing R^2 Score: 0.73
Training RMSE: 6.54
Training RMSE: 6.93
```

On the surface, not terrible results. More alarmingly, the scores varied dramatically on subsequent tests, often going as low as a .50 $R^2$. I suspect overfitting to be a problem here.

### Gradient Boosting Regressor

```python
grid = {'learning_rate': [i / 100 for i in range(1,100, 5)] + [.5, 1],
                'n_estimators': [i for i in range(50, 200, 20)],
                'max_depth': [i for i in range (2, 7)]}
search = GridSearchCV(reg, param_grid = grid, cv = 3)
```

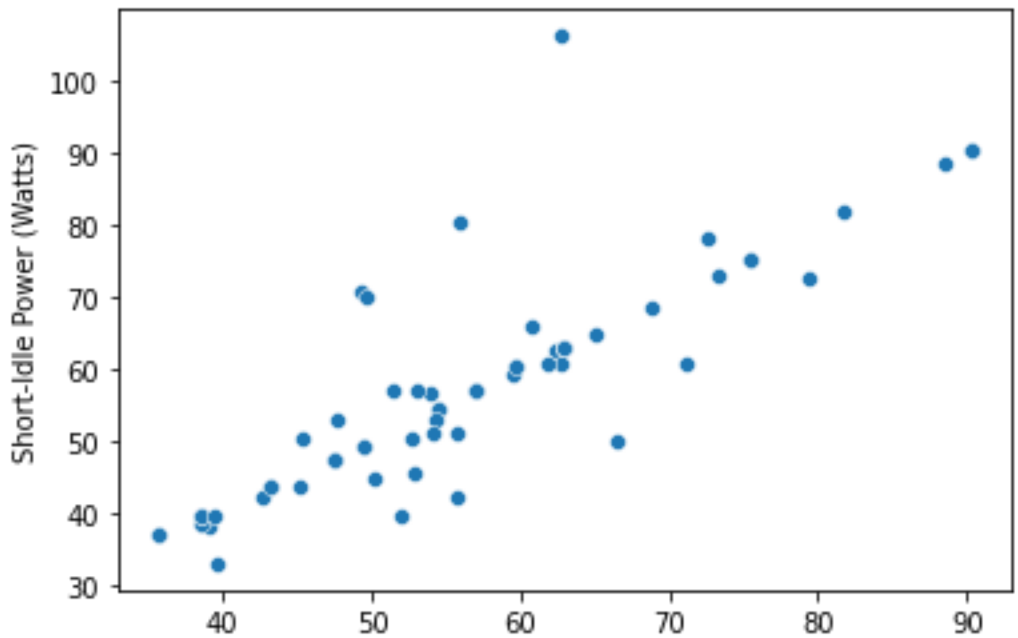
```python
search.best_estimator_
```

```
GradientBoostingRegressor(learning_rate=0.31, max_depth=4, n_estimators=90)
```

Gradient Boosting performed much more consistently: showing some overfitting still, but not quite to the degree I saw with Random Forests. The chosen parameters show a very conservative model in terms of tree depth and number of estimators, but the fact that it used a higher learning rate than normal tells me there might be an issue of imbalance still among the discrete values. I figured more oversampling would lead to even worse overfitting, so I refrained from doing so.

```
Tuned Gradient Boosting Results
-------------------------------
Training R^2 Score: 0.9
Testing R^2 Score: 0.77
Training RMSE: 4.92
Training RMSE: 6.45
```

Overall, not terrible results at all. I wouldn't say this would be satisfactory to replace testing altogether, but it's certainly good enough for a baseline of weeding out combinations that would not pass the CEC's requirements or for outlier detection of fraudulent submissions. The predicted vs actual plot on the test set shows a very promising line:




While I suspect this is the best performing model, perhaps we can prove that a more parsimonious model would be just as effective. I trained one last model using only power supply wattage, chipset, high-expandability score, and GPU bandwidth. These are educated choices given the exploratory stage showing that wattage is strongly linearly related to idle power consumption, as well as high-expandability score being *very* important. I simply had a hunch that GPUs are important, as well as the chipset of the motherboard as newer chipsets are often more power efficient. If a model using just these attributes can perform well, perhaps the CEC could loosen regulations to exclude trivial attributes while reducing labor problems for manufacturers.

**To my surprise**, the parsimonious (simple) model performed ***better***. Not only is there a lot of random noise generated by the added dimensions, but it is also practically useless. This was all I did, and the results are better in every regard: far less overfitting, and better variance explained.

```
scaler = MinMaxScaler()
X = scaler.fit_transform(pd.get_dummies(
    skytech_resampled[
        ['Expandability Score', 'GPU Bandwidth', 'PSU Size (Watts)', 'Chipset']
    ]))
y = skytech_resampled['Short-Idle Power (Watts)']
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size = .3)
grad = GradientBoostingRegressor().fit(X_train, y_train)
print(f"Simple model's training R^2: {round(grad.score(X_train, y_train), 2)}")
print(f"Simple model's test R^2: {round(grad.score(X_test, y_test), 2)}")
```

```
Simple model's training R^2: 0.86
Simple model's test R^2: 0.81
```

## Conclusions

Despite the simplicity and not-so-interesting of a topic, this has by far been my favorite project I have done. It exemplified part of what this profession requires: shedding biases and learning something new.

### Efficacy

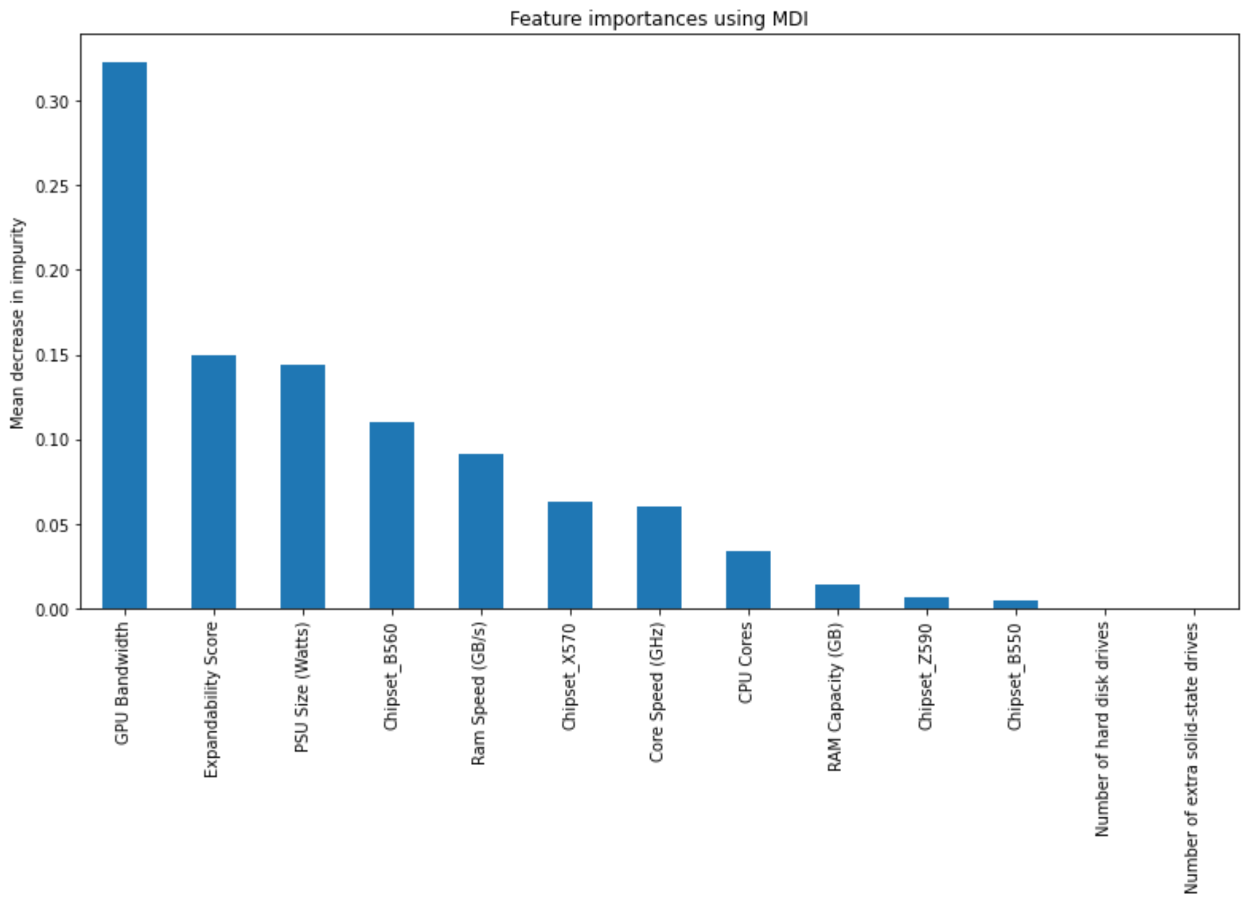
Prior to this project, I fully believed the regulations were well-intentioned, yet the high-expandability requirements were counterproductive in that they made power consumption *worse*. **This turned out to be completely wrong,** shedding my own biases and going against the common sentiments in the industry. I am not an expert on motherboard architecture, but it is encouraging to see that this change will result in significantly less power consumption.

Still, **the High-Expandability Score formula is flawed:** if just as much variance can be explained with fewer attributes, simplify the formula.

As for the 80 Plus Gold requirements, it is completely unnecessary – 80 Plus has long been a controversial labeling, and numerically the Gold power supplies simply aren't much more efficient than the lower, cheaper Bronze power supplies. The CEC should heed the advice of EnergyStar.gov and my own: lower the price for consumers and reduce labor costs by removing this requirement.

So, are these regulations effective? **Yes and no**. The CEC needs to seriously reconsider some aspects of their requirements.

## The Labor Problem




While I didn't expect the model to provide any use outside of the use cases I provided, the most important takeaway I have is that the model proved simplicity is key for balancing the need to lower power consumption and keeping manufacturers happy.

Feature importance from the tuned model proved to be useful in confirming that power consumption is mostly explained by the GPU, the expandability score of the motherboard, power supply size, and chipset. The simple model that was built on these features proves that the CEC missed the mark on the amount of data required for submission: you can account for just as much variance, if not more, by reducing the number of details needed for each submission.

If the CEC were to loosen the requirements on submitted data to only include those 4 attributes, this would dramatically reduce the amount of labor needed for testing. From the example I provided earlier, with a parsimonious model and data requirement, that figure of 210,600 different combinations reduces to just 5,544 total combinations (4 unique chipsets x 11 unique GPU Bandwidths x 6 PSU wattages x 21 unique Expandability Scores = 5,544). This is a miraculously more manageable number of combinations to test, which again maybe only half of which would realistically be used.

The future of the CEC's regulations remains uncertain currently. The deadline for manufacturers to comply is only within weeks at the time of writing this (Nov, 2021), and still many are scrambling to develop procedures to comply with the testing requirements. While I do work for a manufacturer, I care more as a consumer myself than I do as an employee–our margins are the same, the customer is the one that shoulders the price burden. Just this time of year last year, the cheapest entry-level gaming PCs we sold were less than $1000. This year, in part due to the CEC and supply woes due to scalping and worldwide supply shortages, the cheapest is $1800. PC Gaming is a fantastic outlet, and access should not be prohibited by completely unnecessary costs. To the CEC I plead: listen to the public, **keep the good, and revise the bad.**

**References**

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