M3 Challenge 2025

Hot Button Issue: *Staying Cool as the World Heats Up*

Executive Summary

This report presents an in-depth analysis of energy consumption trends, heatwave vulnerability, and temperature in a non-air-conditioned dwelling in Memphis, Tennessee, using advanced statistical modeling techniques. The study is divided into three primary components: the temperature in buildings without AC, forecasting future energy consumption trends, and developing a vulnerability index for neighborhoods in the event of extreme heat waves or power outages. Each section applies quantitative methods to guide decision-making for policymakers and utility companies, ensuring efficient resource allocation and proactive infrastructure planning.

The model predicts indoor temperatures in a non-air-conditioned Memphis home during a 24-hour heatwave, accounting for heat transfer from insulation, windows, and inhabitants. It shows that indoor temperatures are typically higher than outdoor temperatures due to heat retention. Sensitivity analysis on parameters like window count and floor area showed moderate variability. The model works well but is limited by assumptions on room dimensions and lacks consideration for factors like ventilation.

Next, the study looks at historical energy consumption data, extrapolating trends and data from Shelby County and East South Central USA to predict future energy demands in Memphis. Utilizing an additive triple exponential smoothing model in excel by using the forecast.ets function, the analysis identifies seasonal variations and long-term trends in electricity usage. The model projects peak demand to occur in June 2025, with an estimated maximum consumption of 640,184,128.96 kWh. Over the next 20 years, energy consumption is expected to gradually decline due to technological advancements and efficiency improvements, with an estimated decrease of 147,948,413.90 kWh by 2045. While this trend suggests progress in energy conservation, the summer months continue to pose challenges with heightened demand, necessitating preparedness from energy providers. Additionally, this model suggests a constant trend which may not be applicable in all cases and over longer periods of years it becomes less accurate.

The next part of the study focuses on assessing neighborhood vulnerability to extreme heat events. The Analytic Hierarchy Process (AHP) was employed to weigh multiple socio-economic and infrastructure factors, including population size, age distribution, housing conditions, and transportation methods. Positive weights were assigned to characteristics indicating higher vulnerability, such as large populations of elderly and young residents, reliance on walking for transportation, and older housing structures with poor ventilation. Conversely, factors such as high median income, newer homes, and automobile dependence reduced vulnerability scores. The dispersion analysis yielded Q1 as -0.891 and Q3 as 0.624, giving an interquartile range (IQR) of 1.51 (IQR = Q3 - Q1 = 0.624 - (-0.891)). This suggests that neighborhoods with an AHP value (vulnerability score) below -0.891, such as Uptown / Pinch District, fall in the top quartile for heatwave preparedness. In contrast, neighborhoods with an AHP of 0.624 or higher, including Collierville / Piperton, are in the bottom quartile and are less prepared for heatwaves.

These findings offer valuable insights for policymakers and utility companies. Our results demonstrate the hazardous conditions created by abnormal high temperatures during a heat wave. Additionally, the predicted energy trends allow for utility companies to be prepared in high demand months, and more effectively plan for capacity needs.. Finally, the neighborhood vulnerability assessment provides data for targeted interventions and resource allocations.

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Q1: Hot To Go

1.1 Defining the Problem

The first problem asked us to develop a model to predict the indoor temperature of any non-air-conditioned dwelling during a heatwave any time during a 24-hour period in one of the provided cities. We chose to find the indoor temperature of a non-air conditioned building in Memphis, Tennessee.

1.2 Assumptions

1.2-1 **Adults who do not work stay in the dwellings for 16 hours per day relaxing/sitting**

- **Justification:** It's difficult to predict where people who are unemployed or not working spend their time so they are expected to stay home for the purposes of finding the heat they emanate to predict indoor temperature.

1.2-2 **Observations are independent and identically distributed**

- **Justification:** For the purposes of the random forest regression we must assume that the data points we are analyzing are not reliant upon each other (meaning no time based dependencies).

1.2-3 **Inside walls do not significantly contribute to the inside temperature**

- **Justification**: While external walls usually contain insulation, thus hindering heat expansion, internal walls contain drywall, which is not a good insulator [1]. Thus the observer frame of reference can either be adjacent to an external wall or an internal wall.

1.2-4 **All external walls are insulated with fiberglass**

- **Justification**: Most houses in the U.S. are insulated with fiberglass [2]. Thus it is reasonable to assume that all houses are insulated with fiberglass.

1.2-5 **There are no other methods in the house to lower room temperature, besides the impact of humans, windows, and fiberglass emitting heat.**

- **Justification**: It is difficult to predict the impact of these methods, such as: opening a window, using a fan, using ventilation, etc. [4]

1.2-6 **Each house is rectangular, with a width to length ratio of 5:7 and a floor area of around 2,469 ft^2.**

- **Justification**: It is difficult to predict the size of a house. To simplify this, it was assumed that each house was a rectangle and took the dimensions width:length as 5:7, in lieu with the average size of a townhouse, as the authors were not knowledgeable of any other sources that provided house dimensions [3]. Additionally, the average floor area of a new home was around 2,469 ft^2 [5].

1.2-7 **Heat transfer only occurs between the roof, walls, and the environment, not from the ground**

- **Justification:** Because the ground has a high heat capacity, even when compared to fiberglass, this means that the floor will not contribute significantly to heat transfer from the environment into the house [6].

1.2-8 **There are an average number of 8 windows in an American home, and each window is 24 in wide x 36 in long.**:

- **Justification**: Windows have a significantly larger thermal conductivity than fiberglass (1.05 and 0.04 respectively) and the heat transfer into the home. However it is difficult to assume the relative amount or size of windows on the walls of a house in Memphis, so as a result we decided on using the average number and size of windows in the U.S. (8 and 24 in x 36 in, respectively) [8, 9].

1.2-9 **The initial inside temperature is assumed to be the same as the initial outside temperature.**

- **Justification**: For ease of calculations, the initial inside temperature is equal to the outside temperature. Additionally, the problem implies that the 24-hour heat wave begins around the same time that air conditioning is lost, meaning that both external and internal temperatures were about the same.

1.3 The Model

1.3.1 **Developing the Model**

When choosing a model for this situation, we decided to use the equation $q = mc\Delta T$, where q is the amount of heat (J), m is the amount of substance (m), and ΔT is the change in temperature, or $T_i - T_0$, where T_i is the inside temperature and T_0 is the outside temperature. We utilized this equation because through some rearranging, it was possible to solve in terms of ΔT:

$$\Delta T = \frac{q}{mc_p}$$

Note that because $m = \rho V$, we can substitute this into our equation above.

Converting both sides to a differential form, we can get:

$$\frac{dT_i}{dt} = \frac{q}{\rho c_p V}$$

This equation is useful because it included time (t), which we could use. However, we still needed T_0. To do this, we integrated both sides over time:

$$\int_{T_i(0)}^{T_i(t)} dT_i = \int_0^{\Delta t} \frac{q_{in}}{\rho c_p V} dt$$

$$T_i(t) - T_i(0) = \frac{q_{in}}{\rho c_p V} \bullet \Delta t$$

However, if we assume that $T_i(0)$ is equal to T_0 (see assumption 1.2-9), one can see that:

$$T_i(t) = T_0 + \frac{q_{in}}{\rho c_p V} \bullet \Delta t$$

We will use the variables q_f (amount of heat transferred into house from the fiberglass insulation), q_h (amount of heat transferred into house from the fiberglass insulation), and q_g (amount of heat transferred into the house from the glass). Additionally, because Δt is in seconds but the data was given in hours [10], $\Delta t = 3600t$, where t is in hours. It is also important to include $\rho = \frac{P}{RT}$, where R=287.05 (J/kg), T is temperature (K), and P is pressure (Pa). P can depend on the temperature (in this case, temperature outside, or T_0), the molar mass of air (M) and height above sea level of the environment (h), and $P = P_0 \bullet e^{\frac{-Mgh}{R \bullet T_0}}$, where R=8.314$J \bullet mol^{-1}K^{-1}$. It is also important to not that each

$q = -\frac{kA(T_i(t)-T_0)}{d}$, where d is the thickness of the material, A is the surface area of the surface that heat transfers through, and k is the thermal permittivity[1]. Finally, V (volume) is equal to Putting all these variables together, we can get:

$$T_i(t) = T_0 + \frac{(q_f+q_h+q_g)}{\frac{c_p V P_0 \bullet e^{\frac{-Mgh}{R \bullet T_0'}}}{RT}} \bullet 3600t$$

However, it is required to use an approximation of T_0' on the right hand side of the equation in order to solve the equation without rewriting to solve for T_i, and allows the formula to be calculated in a spreadsheet without returning a circular reference error. This approximation was optimized, and as a result, we estimated that T_0' was indeed 85℉, or 302.5944 K.

We then used the provided data on temperatures recorded during a heat wave during the 24-hour period.

1.4 Results

The model is as follows:

$$T_i(t) = T_0 + \frac{(q_f+q_h+q_g)}{\frac{c_p V P_0 \bullet e^{\frac{-Mgh}{R1 \bullet T_0'}}}{R2To}} \bullet 3600t$$

Where

- T_i represents the outside temperature in $Kelvin$
- T_0 and To represent the outside temperature in $Kelvin$
- q_f represents the heat transfer rate of fiberglass in $\frac{Watts}{Meter\ kelvin}$
- q_h represents the heat transfer rate of the building's inhabitants in $\frac{Watts}{Meter\ kelvin}$
- q_g represents the heat transfer rate of glass in $\frac{Watts}{Meter\ kelvin}$
- c_p represents the specific heat capacity of air in $\frac{Joules}{Kilogram}$
- V represents the Volume of the building in $meters^3$
- P_0 represents atmospheric pressure in $Pascals$
- M represents the molar mass of air in $\frac{Kilograms}{Mole}$
- g represents the acceleration due to gravity in $\frac{meters}{seconds^2}$
- h represents the elevation of Memphis in $meters$
- $R1$ represents the universal gas constant in $\frac{Joules}{Mole * Kelvin}$

[1] Specifically, q sub h was calculated through the following: employed people (47.05%) had an estimated 8 hours of leisure time (that they spent in the house), unemployed people (52.95%) had an estimated 16 hours of leisure time (that they spent in the house). For both individuals, 70 watts of energy was assumed to emit from these individuals during sleeping, and 100 watts of energy was assumed to emit from these individuals during leisure time. Using the k value for humans, q sub h was obtained [6.5].

- T'_0 represents the approximated inside temperature in $Kelvin$
- $R2$ represents the specific gas constant of air in $\frac{Joules}{Kilogram * Kelvin}$

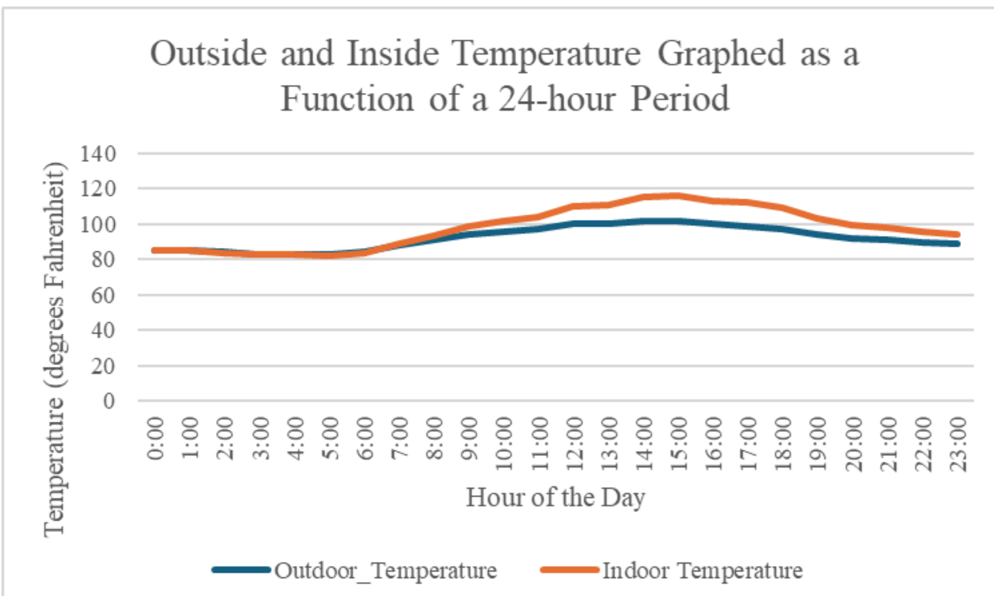
And for q_f and q_g

$$q = \frac{kA(Ti-To)}{d}$$

Where

- q represents heat transfer rate in $Watts$
- k represents the thermal conductivity of a material in $\frac{Watts}{Meter\ kelvin}$
- A represents the surface area being heated in $meters^2$
- Ti represents the approximated inside temperature in $Kelvin$
- To represents the outside temperature in $Kelvin$
- d represents the thickness of the surface being heated in $meters$

Figure 1:



This graph demonstrates the outside and inside temperature as a function of a 24 hour period.

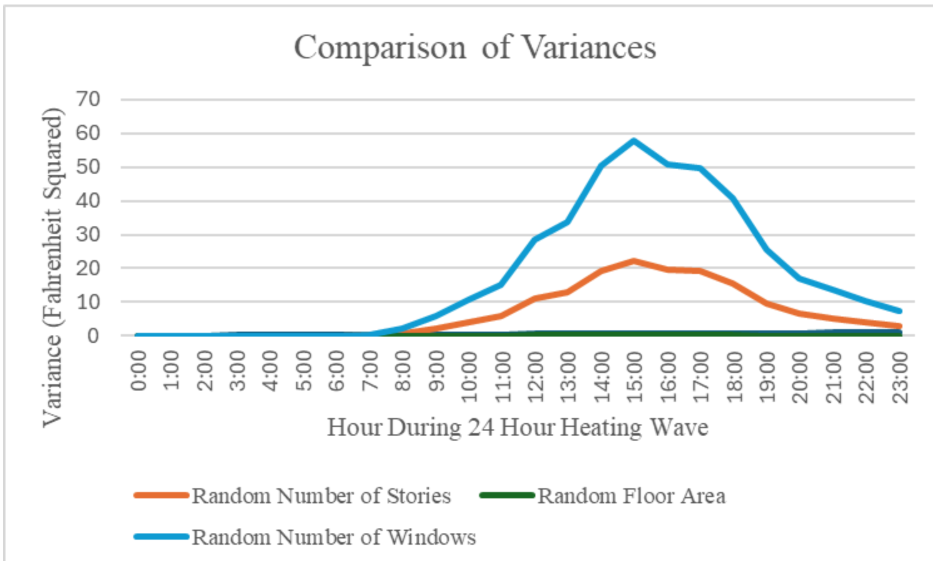
1.5 Discussion

For a suburban house in Memphis, our model will predict a higher inside than outside temperature most of the time during a 24-hour heating wave, from 0:00-1:00 and from 7:00-23:00, which highlights the utility of proper insulating material in its goal of diminishing rises in temperature in the building. The trends in indoor temperatures follow that of outdoor temperatures; for example, the highest separation between the inside and outside temperature, at 14.16052℉, occurred at 15:00, yet the indoor temperatures do not seem to subside at the same rate as the outside temperatures. Rather, the model suggests that buildings seem to accumulate heat which they radiate into their interior over time; despite losing heat through means such as windows, a majority of the heat gained is trapped inside by the insulating material, keeping temperatures higher than that outside.

1.6 Sensitivity Analysis

To determine the accuracy of our predicted model, sensitivity analysis was conducted on it. We changed the parameters, and the jittered variance was calculated. Three parameters were selected: the number of stories, the number of windows, and the floor surface area, as these parameters were most likely to vary between house to house.

Figure 2: Comparison of Variances for Certain Parameters



This graph demonstrates the variance, in °F^2, when the number of floors, the floor area, and the number of windows is altered.

1. Because the tallest apartment in Memphis is 25 floors tall [8.5], a number of floors was randomly chosen between 1 and 25, and inside temperatures were calculated over the hypothetical 24 hour heat wave period. This was repeated 10 times. As seen in the graph, the highest variance observed was around 20 °F^2 (24%), meaning that the model was relatively moderately prone to error.
2. Because house floor plan can vary drastically, we randomly offset the "ideal" floor plan area (2,469 ft^2) by 5% either way, and inside temperatures were calculated over the hypothetical 24 hour heat wave period. This was repeated 5 times. As seen in the graph, the highest variance was around 0.209559055 °F^2 (0.24654%), that the model was relatively unlikely prone to error.
3. Because the number of windows can vary drastically from house to house, such as an average of 22 windows found by the EPA [7], a number of windows was randomly chosen between 1 and 22, and inside temperatures were calculated over the hypothetical 24 hour heat wave period. This was repeated 10 times. As seen in the graph, the highest variance observed was around 50 °F^2 (59%), meaning that the model was relatively extremely prone to error.

1.7 Strengths and Weaknesses

The model worked very well in accounting for multiple variables and using them adequately, and can be changed to model buildings of different square footage and number of stories. However, the model is held back by the availability of data relating to room dimensions. The model assumes that each room is a rectangle with one window for every two walls, very much standardizing the nuanced architecture of Memphis. Additionally, the model fails to consider the effects of ventilation, which can circulate outside and inside air together, thus decreasing the interior temperature had there not been any ventilation, and solar gain, where sunlight entering through the windows can bring in warmth and increase the internal temperature significantly.

When discussing the importance of these findings, it is important to note from the graph that while lower outside temperatures (e.g. 80-85℉) do not result in vastly different interior temperatures, as the temperature rises in a heat wave (e.g. 100-120℉), do result in vastly different interior and exterior temperatures. This demonstrates that heat waves are extremely dangerous, as it can lead to unbearable and potentially hazardous temperatures to human life. However, the analysis of variance also demonstrates the high dependency of interior temperature on the number of windows and the number of stories to the building. Further research with lesser time constraints could investigate stronger models that could be less sensitive to parameter changes, as mentioned previously.

Q2: Power Hungry

2.1 Defining the Problem

The second question asks us to predict the peak demand that the city's power grid needs to be able to handle during summer months as well as changes in maximum demand 20 years from now. We looked at various trends in data to extrapolate an estimate for monthly energy consumption in the city of Memphis, Tennessee, as well as how the demand would change.

2.2 Assumptions

2.2-1 **The per-capita energy usage in Shelby County is equal to the per-capita energy usage in Memphis, with negligible difference.**

- **Justification:** Data for energy usage for specific cities is extremely limited, and therefore isn't sufficient to be able to come up with accurate predictions. Moreover, Memphis accounts for the majority of the Shelby County population, and therefore any differences in per-capita energy usage between Memphis and Shelby County are likely negligible. Since Memphis constitutes the majority of the county's population, its energy consumption patterns dominate the overall county's trends. As a result, even if there are slight variations in energy usage between Memphis and other parts of Shelby County, these differences are unlikely to significantly affect the overall per-capita average.

2.2-2 **Examined monthly trends in energy consumption in Shelby County are similar to trends in the East South Central US region (encompassing Alabama, Mississippi, Tennessee, and Kentucky.)**

- Justification: Month by month data for Shelby County is not easily accessible, making it difficult to determine monthly trends in Shelby County. Moreover, weather patterns in Shelby County can be assumed to be similar to those of the East South Central U.S. region, as both share similar geographical conditions such as humidity, sunlight exposure, and proximity to large bodies of water. Due to this proximity, Shelby County experiences comparable seasonal energy demands, leading to similar energy consumption trends. The ratio for the change in months for energy consumption should therefore be constant across all regions included in the east south central US.

2.2-3 **There will be no major innovative changes affecting energy consumption.**

- **Justification:** Major inventions in energy use would significantly impact overall energy consumption. However, it is practically impossible to predict when these innovations will occur or how they will affect energy usage. Additionally, since our model is based on trends from 2012-2022, it accounts for gradual improvements in energy efficiency.

2.2-4 **Consumer energy use trends will remain consistent in the future**

- Justification: There was not enough time to accurately identify the effect of campaigns and movements on climate change on energy consumption. The model predicts future data off of historical data, so it is assumed that the data will follow the general trend over 2012-2022 and that no new social movements will massively change the energy consumption of citizens in Memphis, Tennessee, Shelby County, or the east south central US region.

2.2-5 **Population trends of Shelby County and Memphis, Tennessee will not drastically change in the future**

- Our model works off the assumption that the population of these two areas will not be drastically reduced or increased for any reason and continues to follow the general trends from 2012-2022. Population of these two regions should not drastically change unless events such as natural disasters or major diseases take place, which we consider too random to consider.

2.2-6 **Current temperature trends and weather patterns will not significantly vary from the past, and people will react to these trends in similar ways**

- Predicting future climate changes is challenging, as the effects of climate change movements are difficult to anticipate. Temperature fluctuations will impact energy use, such as increased reliance on air conditioning as temperatures rise. Since our model is based on existing energy consumption data, we assume that climate patterns will remain relatively consistent and that people will adjust their energy use in ways similar to the past. Climate change has driven rising temperatures for many years, leading the model to predict that this trend will continue. However, this assumption has limitations.

2.3 The Model

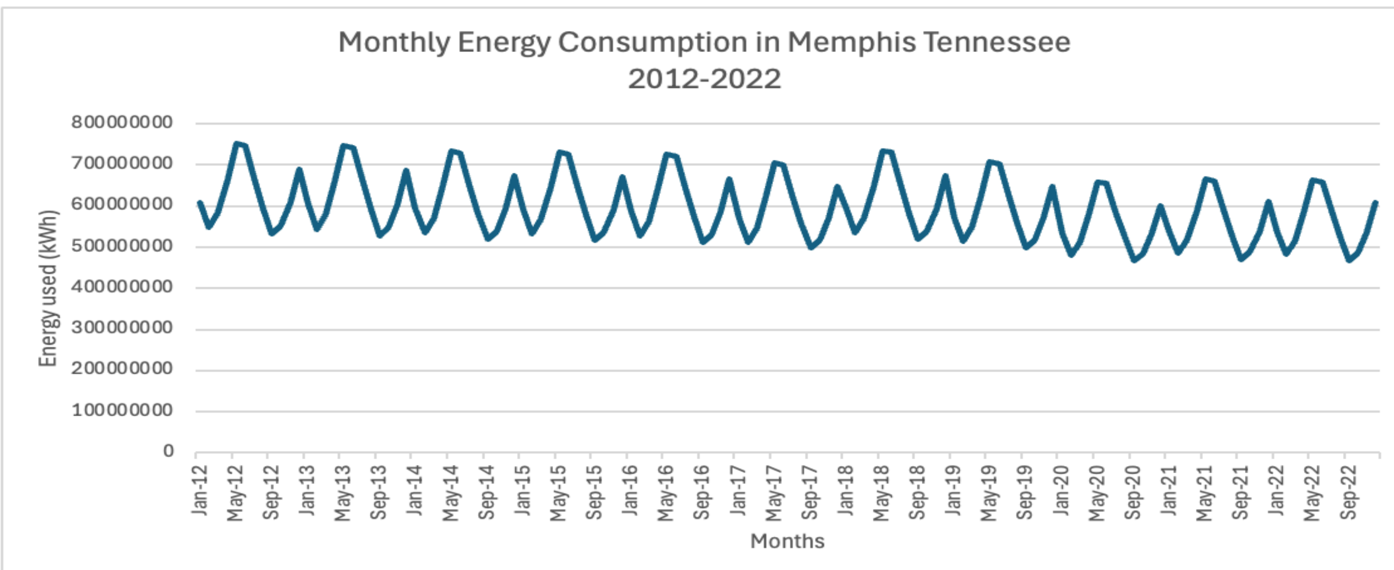
2.3.1 Developing the model

For this dataset, we chose an additive triple exponential smoothing forecasting model in Excel spreadsheets. Triple exponential smoothing is particularly useful for time series data that exhibit both trends and seasonality, making it ideal for our dataset, as energy consumption typically follows long-term and seasonal trends. Other models such as a linear regression or logistic curves would not be able to show seasonality and cannot give us the full trend data.

To generate our dataset, we first obtained total monthly energy consumption data for the East South Central U.S. states [10] and calculated the month-to-total ratio for 2024 by dividing each month's consumption by the total annual consumption (Appendix F). We assumed this ratio remained constant over time and applied it to Shelby County, considering its monthly energy consumption patterns to be identical to the regional trends. Next, we multiplied Shelby County's yearly energy consumption from 2012 to 2022 [10] by each month-to-total ratio to estimate monthly energy consumption values for those years (Appendix F). These monthly energy values were then divided by Shelby County's population [12] for each respective year to determine the per capita energy consumption (Appendix G). Assuming that Memphis, Tennessee, has the same per capita energy consumption as Shelby County, we multiplied these values by Memphis's population [12] to estimate monthly energy consumption in Memphis from 2012 to 2022 (Appendix E).

We then graphed this data, allowing us to analyze trends and justify our choice of forecasting model.

Figure 3: Graph of monthly energy consumption in kWh in Memphis, Tennessee, vs the various months (Month-20XX) with extrapolated data.



Shows trends in monthly energy consumption from 2012-2022, by plotting the extrapolated data points on a graph

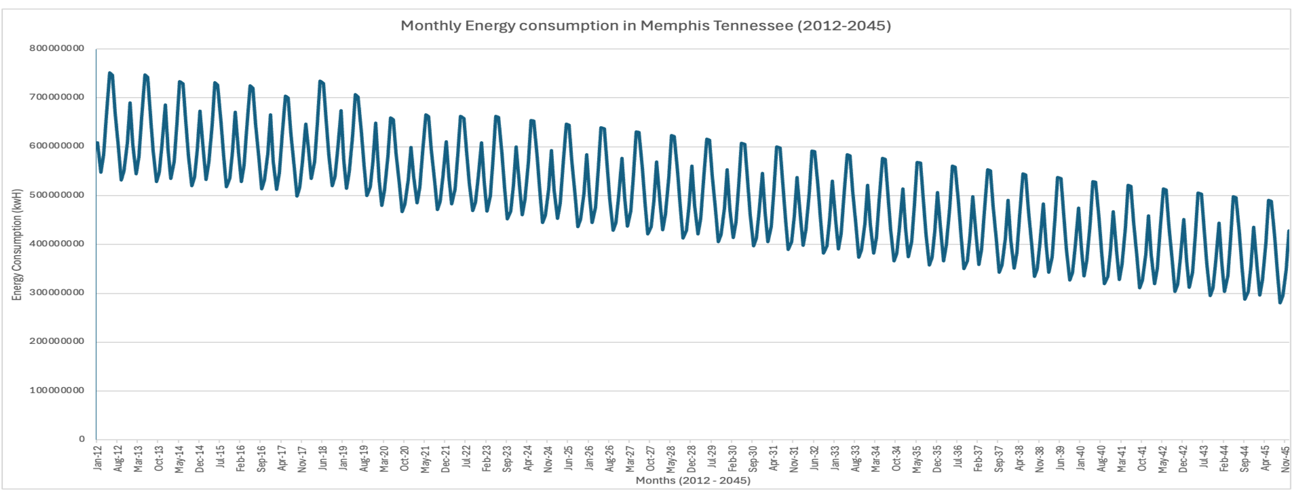
From the graph, we observe a clear seasonal trend. There are energy consumption peaks in the summer months (around June) and declines during moderately cool months, like February and September. Additionally, overall energy consumption appears to be gradually decreasing over time.

Given these patterns, we used triple exponential smoothing, which accounts for both seasonality and trends, to produce accurate future predictions. Furthermore, we employ the additive version of the triple exponential smoothing model because the seasonal variations remain relatively constant rather than fluctuating in magnitude over time.

2.3.2 Executing the model

Excel spreadsheets provides a function called “forecast.ets” which predicts future values off of historical values by using the additive version of the exponential smoothing algorithm. This is Excel's function for triple exponential smoothing. The function is additive because seasonality is constant and so are trends, which is seen in Figure 3. Using the Excel forecast functions, there are 5 parameters which we need to enter: The target date, the list of energy consumptions by month for all known values, the corresponding dates of the energy consumption, the seasonality, data completion, and aggregation. The seasonality is 12 because repetition of the peaks and troughs happens yearly. The historical data is fully complete as there are no missing values, so we can enter a 1, and the type of aggregation is an average, so that value is also a 1. We can input the values for our monthly energy consumption by month found in the earlier development to this forecast, using the known values of energy consumption corresponding to their specific month, the target date for our prediction, the seasonality, the data completion, and the data aggregation values. Using the same data for every date and only changing the target date in the forecast.ets formula until we reach December 2045 gives us our predicted values for every month between December 2022 and December 2045. Plotting a graph of these values vs the given months will give us the expected trend for energy consumption by month in Memphis, Tennessee:

*Figure 4**:** graph of energy consumption in kWh by month in Memphis, Tennessee.*



The graph shows increasing and decreasing trends throughout the year as well as a decreasing overall energy consumption over the next 20 years.

Our model equation for this situation will have two variables: the amount of time after the initial set of data in months and the seasonal factors. There are various other equations that have to be calculated but because of the complexity we were not able to get a specific value.

Figure 5:

Symbol	Variable	Unit
m	Seasonal smoothing coefficient	N/A
S	Seasonal factors	N/A
α	level smoothing coefficient	N/A

β	Trend smoothing coefficient	N/A
γ	Seasonal smoothing coefficient	N/A

Table of variables used in our model development

To derive an equation for our model and analyze sensitivity on this test we ran the original data set through a series of codes to determine the optimal alpha, beta, and gamma values. The equation for exponential smoothing is complex, consisting of multiple parts that are eventually combined together to create a final formula.

$$\text{(Level) } L_t = \alpha * (Y_t - S_{t-s}) + (1 - \alpha) * (L_{t-1} + b_{t-1})$$
$$\text{(Trend) } b_t = \beta * (L_t - L_{t-1}) + (1 - \beta) * b_{t-1}$$
$$\text{(Seasonal) } S_t = \gamma * (Y_t - L_t) + (1 - \gamma) * S_{t-s}$$
$$\text{(Forecast for period } m\text{) } F_{t+m} = L_t + m^*b_t + S_{t+m-s}$$

These are the 4 parts of the triple exponential smoothing equation, where alpha is the coefficient for level smoothing, beta is the coefficient for trend smoothing, and gamma is the coefficient of seasonal smoothing. Running our original data set through a series of code in google co-lab calculates the optimized coefficients for the equation and fits them into the final equation. This optimization method chooses the best parameters for our model to assure accurate results and calculations (Appendix F). The finalized equation for our model is:

Figure 6: Forecast Equation

$$F_m = (547682731.9 + (m * -616451.7246)) + S_T$$

Equation, which finds the forecasted energy consumption in a certain month based on seasonality and months since December 2022.

Where F_m is the forecasted value, m is the amount of months after December 2022. Seasonal factors compare the specific data value with the forecasted data value. Seasonal factors are constant for every month because we are using triple exponential smoothing and seasonal trends should be constant. To calculate seasonal factors, a code script was run to calculate the trend by using a moving average to estimate the trend and then subtract the trend from the observed values to isolate seasonality. It then averaged the seasonal values for each month over all years and normalized the seasonal components so they sum to zero to give us our values for the seasonal factors.

Table 7: table of calculated seasonal values for our model

Month	**Seasonal Factors**
January	-22178994.82
February	-79081952.41
March	-45083242.81
April	30163132.82
May	115135446
June	110994948.8

July	38977596.92
August	-30176925.26
September	-90304856.17
October	-71618126.19
November	-17668884.14
December	60841857.28

2.4 Results

Running the data through the Forecast equation (Figure 6) gives us several data points as well as giving us an equation for forecasted values based on months. To find the maximum demand of energy consumption that the Memphis power grid would be required to handle, we can look at the highest peak in Figure 4 past the current date. As such, we conclude the highest energy consumption for the future is in June 2025 (Figure 4). To find the specific energy consumption, we use the Forecast equation $F_m = (547682731.9 + (m * -616451.7246)) + S_T$. Using June's seasonality factor and the month of June 2025, we find Fm = (547682731.9 + (30 * −616451.7246)) + 110994948.8),=640,184,128.962. As such, in preparation for the summer months, the power grid should be able to handle 640,184,128.962kWh. Next, we can use Figure 4 to conclude how the max demand will change over the next 20 years. Observing the general trend, we can conclude that the max demand will decline over the years, with an estimated decrease of 147,948,413.904 by 2045 (485,955,292.5258 in March 2025 to 338,006,878.622 in March 2045), as per the Forecast equation.

2.5 Discussion

Our model indicates that energy consumption hits its peak during the summer months around May and June, and hits its lowest values in fall and winter months such as February and September, and predicts a general decrease in energy consumption as the years go on. Based on the past trends of the data, the energy consumption is decreasing. Our model accounts for variables such as innovation and temperature on a small scale by assuming they follow the same trends as historical values, meaning that as long as temperature and innovations follow similar trends as historical data and do not change drastically our data will be valid.

Our results provide valuable insight for policymakers and utility companies. Providing the maximum energy demand allows for utility companies in Memphis to be prepared for energy demands without being overwhelmed. Furthermore, by showing that over time, energy consumption is seen to decrease, policymakers and utility companies can shift focus to other infrastructure over time, and invest in other industries. Furthermore, the seasonal trends give utility companies ideas about how energy consumption changes throughout the year, allowing them to be prepared for increases or decreases in energy consumption throughout the year. The specific results provide deeper insight into specific predicted energy usage. According to our model, as long as there are no unexpected increases in temperature, energy consumption should continuously decrease over time. As such, it seems to show that while temperatures have been steadily increasing with climate change, factors, such as steady improvements in technology, have been decreasing energy consumption. Therefore, it appears that the issue about energy consumption will, by itself, face improvements. However, summer months still show high energy consumption values, even in later years, showing a need for preparation from utility companies for these months.

2.6 Strengths and Weaknesses

Since our data is a time series with consistent trends throughout the years, an additive triple exponential smoothing model fits the requirements to accurately show the results and trends throughout the separate years and show a trend overall. This model effectively shows the trends in the months by using different values for seasonal factors and months as well as showing a decreasing overall trend for the energy consumption in total, allowing us to observe and analyze data across the years and throughout the years. One of the main things that can weaken exponential smoothing is the selection of the alpha, beta, and gamma parameters, since using the wrong ones will cause different results. Using a code script to optimize the results to give us the smallest amount of error helps us get the best values for our parameters to insert into our equation.

However, exponential smoothing cannot predict accurately very far into the future. The optimal range for exponential smoothing would be about 5-10 years, which we went far past. Additionally, we did not have enough time to account for additional variables that could have affected energy output, like views on energy consumption or temperature trends. Additionally, exponential smoothing cannot handle sudden disruptions in the data. This model works off the assumption that future data will proceed similarly to historical values in the same trend and assumes constant seasonality, though for this situation, seasonality should change very slightly. A better model, if we had more time, could be to do an exponential smoothing equation with multiple independent variables to account for temperature, cost, and populations that could affect the variables. Other models such as a Seasonal ARIMA that is adjusted for multiple independent variables would have been more accurate and offered a better scope for the data. However, we were not able to implement these methods because of the complexity and time constraints.

Q3: Beat the Heat

3.1 Defining the Problem

The third problem asked our team to develop a vulnerability score for each neighborhood with the goal of equitably allocating resources especially to those in need. These scores would come into play in the event of an extreme heat wave or power grid outage. In addition, we were asked to present an approach to how Memphis can incorporate the vulnerability scores into their heat wave management strategies.

3.2 Assumptions

3.2-1 **The criteria being judged are independent from one another.**

- **Justification:** In accordance with the Analytic Hierarchy Process we must assume that none of the variables are dependent on one another so the results from the model can be valid.

3.2-2 **The criteria weighting reflects the relative importance of each factor on the need during a heatwave.**

- **Justification:** In reality needs can be based on a case-by-case basis, but by generalizing each potential need and ranking it by its perceived relative importance we can estimate the total need of a neighborhood without having to individually analyze each case.

3.2-3 **The scores are linearly scalable and meaningful and do not distort the real world significance.**

- **Justification:** We are assuming that by scaling and normalizing the values linearly it doesn't distort the real world effect of the needs during a heatwave. For example, having a very low income is significantly worse than having a slightly below average income, but this could not be recognized by this particular model.

3.2-4 **The combined effects of the model are additive.**

- **Justification:** We assume by using this model that the individual effects contributing to need in a heatwave are still relevant when added because this model calculates the vulnerability score by adding the weighted needs of all the values.

3.2-5 **Analytic Hierarchy Process Captures All Relevant Factors**

- **Justification:** This model assumes that all the major relevant factors in determining need in the event of a severe heat wave are included in the model. If a factor is missing it's possible that the model may be incomplete.

3.3 The Model

3.3.1 Model Development

To best answer this question, we used the Analytic Hierarchy Process (AHP), a structured decision-making framework used to determine the relative importance (weights) of multiple factors when making complex decisions, to create the vulnerability scores for each neighborhood [13]. Factors are identified as a value between -1 and 1 based on their relative importance or unimportance to the vulnerability index at hand and combined they must add to 1. A score of 1 meaning significant importance to needing funds and a score of -1 meaning significant unimportance to needing extra funding. The scores given to a given factor are indicated by the number in parenthesis.

First, we determined which factors affected the need of a neighborhood in the event of a heatwave and weighed them based on their relative importance or unimportance to promote equity in fund allocation. For factors we thought would need extra fund allocation we weighted positively and higher on the scale. We said that Population, Households with one or more people 65 years and over, Households with one or more people under 18 years, Primary mode of transportation to work (persons aged 16 years+) walking, Homes built 1970 to 1989, Homes built 1950 to 1969, Homes built 1950 or earlier, and Detached whole house as indicators that these neighborhoods needed extra funding allocation due to their susceptibility to heat. A neighborhood with more people (0.40) overall means there are more potential victims and therefore a greater necessity of funds. Elderly (0.30) and younger people (0.25) are more vulnerable to heatwaves so having a greater population of these people increased a neighborhood's vulnerability score. Having walking as the main way of transportation (0.10) means more pedestrians which in turn indicates more heat exposure. Finally, older homes (0.10, 0.15, 0.20, 0.25) and detached homes have worse ventilation meaning that they need more support in the event of a heatwave. We used the data provided in the MathWorks Math Modeling Challenge 2025, curated data [10].

Then, we selected the factors that indicated a lack of need including: Population with Bachelor's degree or higher (-0.15), Median household income (in US dollars), Primary mode of transportation to work (persons aged 16 years+): driving, and Homes built 2010 or later. Having a bachelor's degree correlates with having more knowledge and resources to deal with a heatwave. Having a higher median household income means having greater access to resources during such an event. Then, driving (-0.15) was an advantage in a heatwave because it kept one out of the sun. Finally, we listed Homes built in 2010 or after because these houses have improved insulation which is better for keeping cool and avoiding heat stroke.

Neighborhoods included in the model: Coro Lake / White Haven, East Memphis – Colonial Yorkshire, Frayser, Egypt / Raleigh, South Memphis, Bartlett, Zipcode 2, Collierville / Piperton, East Midtown / Central Gardens / Cooper Young, Cordova, Zipcode 1, Lakeland / Arlington / Brunswick, Hollywood / Hyde Park / Nutbush, Windyke / Southwind, Cordova, Zipcode 2, East Memphis, North Memphis / Snowden /New Chicago, Midtown / Evergreen / Overton Square, Bartlett, Zipcode 3, South Riverdale, Germantown, Zipcode 1, Bartlett, Zipcode 1, Uptown / Pinch District, South Forum / Washington Heights, Oakland, Downtown / South Main Arts District / South Bluffs, Germantown, Zipcode 2, Rossville, Hickory Withe.

Final Equation for AHP [14]:

$$S_j = \sum_{i=1}^{n} w_i x_{ij}$$

- S_j is is the final score for alternative j
- w_i is the weight of criterion i
- x_{ij} is the performance of alternative j in criterion i

3.3.2 Model Execution

To execute this model we utilized the python code listed in Appendix B to generate the raw data listed in Appendix A. We used the data provided in the MathWorks Math Modeling Challenge 2025, curated data to create the raw data [10]. To utilize the AHP model in the most effective way we utilized the dependencies pandas, numpy, os, and zscore. We ran models with multiple different weights for different factors (Including: Population, Median income, Mode of transport, and Age of House), but we settled on these values because we thought the APH scores more accurately represented the neighborhood's actual need in the event of a heatwave.

The method of finding the dispersion of the model is Interquartile Range (IQR) which measures the bottom and top quarter of the data (as Q1 and Q3) to find the spread in the middle of the data. In this instance the Q3 would need the most help during a heatwave and Q1 would need the least help in terms of funding. This is an important step because it could help a local legislature differentiate between who's well off and who's not with a very clear and concise metric to help allocate resources more effectively. IRQ=Q3-Q1.

3.4 Results

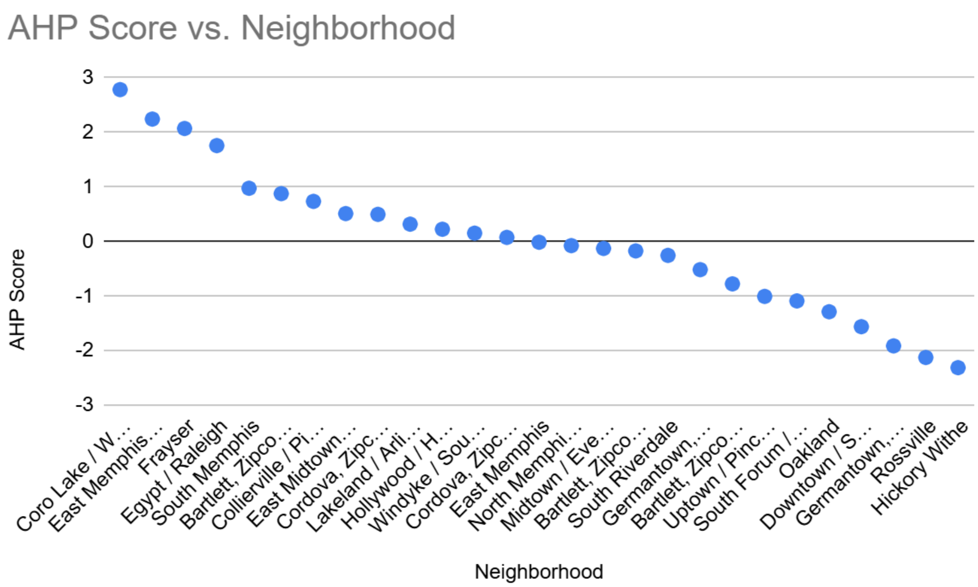
Figure 7: AHP (vulnerability) scores and neighborhoods

Neighborhood	AHP Score (Vulnerability Score)	Neighborhood Cont,	AHP Score Cont.
Coro Lake / White Haven	2.782739055	North Memphis / Snowden / New	-0.07527081364

		Chicago	
East Memphis – Colonial Yorkshire	2.242995109	Midtown / Evergreen / Overton Square	-0.1266843305
Frayser	2.070867369	Bartlett, Zipcode 3	-0.1721028342
Egypt / Raleigh	1.757415879	South Riverdale	-0.2544263029
South Memphis	0.9756716795	Germantown, Zipcode 1	-0.5155874691
Bartlett, Zipcode 2	0.8767937271	Bartlett, Zipcode 1	-0.7757207563
Collierville / Piperton	0.7355064008	Uptown / Pinch District	-1.005888846
East Midtown / Central Gardens / Cooper Young	0.511622048	South Forum / Washington Heights	-1.088127741
Cordova, Zipcode 1	0.4970329017	Oakland	-1.286871555
Lakeland / Arlington / Brunswick	0.3180753143	Downtown / South Main Arts District / South Bluffs	-1.56032771
Hollywood / Hyde Park / Nutbush	0.2245697538	Germantown, Zipcode 2	-1.912157699
Windyke / Southwind	0.1527953237	Rossville	-2.124292456
Cordova, Zipcode 2	0.0753290764	Hickory Withe	-2.310858494
East Memphis	-0.01309662882		

The table lists the AHP (neighborhood vulnerability score) of all the neighborhoods in Memphis, Tennessee.

Figure 8: AHP Score vs. Neighborhood

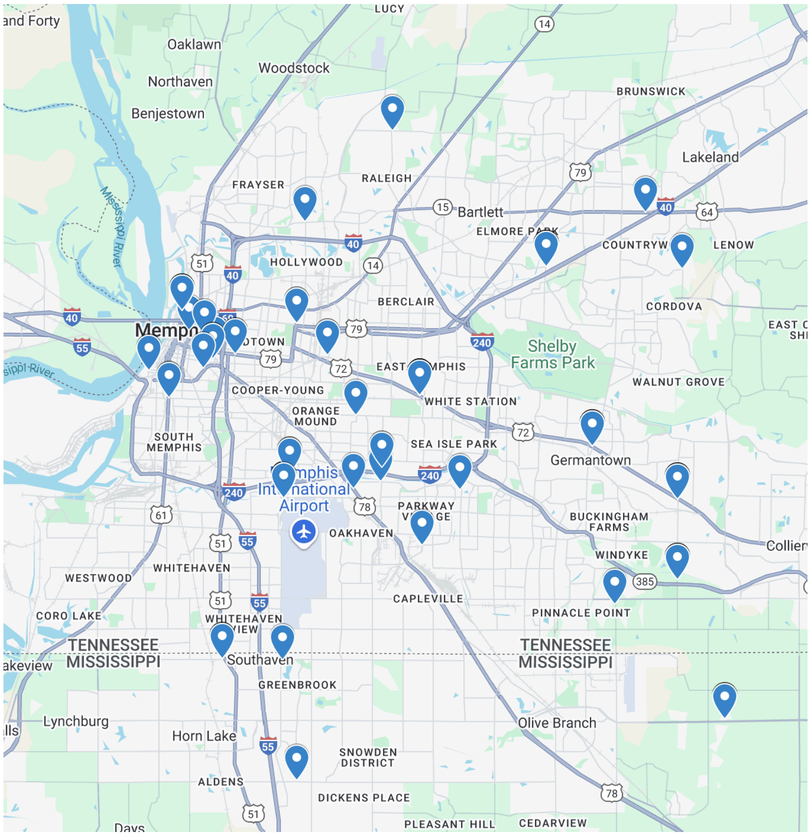


This figure shows the AHP scores in different neighborhoods, showing the distribution for the included neighborhoods

3.5 Discussion

This data suggests that Hickory Withe is the best off in the event where there is in the event of a heatwave in Memphis, Tennessee and Coro Lake / White Haven would need the most additional allocative funding. Based on our model, the city of Memphis should take action to address the differences in AHP scores and balance them. The AHP scores correlate with a neighborhood's vulnerability during a heat wave, with high scores representing a drastic need for intervention and low scores presenting an opportunity to scale back relief efforts. Specifically, city officials should direct large scale investment into heat wave-alleviation efforts, given their need and the city's surplus budget from power infrastructure. We propose that the city of Memphis facilitate citywide oases, locations where citizens can find shelter from the sun and get hydrated. This can be accomplished through partnerships and subsidy agreements with existing gas stations, like Shell and Marathon. Leveraging connections between these existing and well-established locations, the city can provide an effective number of easy to access oases. Given the gas stations' frequency and the large number of drivers in Memphis, subsidizing gas stations to hand out free and cheap beverages while allowing residents to enjoy the comfort of their air conditioning could prove an effective measure to combat the aggressive heat of the area. Additionally, giving gas stations tax breaks on AC bills would incentivize and allow more gas stations to help residents passing by.

Figure 9: Gas stations in the Memphis area



[2]

Gas stations in the Memphis, Tennessee area.

The dispersion analysis resulted in Q1 being -0.891 and Q3 being 0.624. This means that the IRQ is IQR = Q3 - Q1 = 0.624 - (-0.891) = 1.51. This means that the most well off neighborhoods are those with an AHP value (vulnerability score) of over -0.891 which indicates that Uptown / Pinch District and below (<-0.891) are in the top quarter of neighborhoods in terms of heat wave preparedness. And on the other hand, neighborhoods with an AHP of 0.624 or higher are in the bottom quarter of neighborhoods in preparedness; this indicates that Collierville / Piperton and above on Table 6 are not prepared.

3.6 Advantages and Disadvantages

This model has many advantages considering it's analytical and multivaried. The model incorporates multiple socio-economic and infrastructural factors (e.g., population demographics, housing conditions, transportation methods), allowing for a more holistic assessment of neighborhood vulnerability. By using the Analytic Hierarchy Process (AHP), the model provides a systematic and quantitative approach to determining vulnerability, reducing bias in decision-making. The model prioritizes neighborhoods with the highest vulnerability scores, ensuring that resources are directed where they are most needed during a heatwave or power grid failure.

This model isn't perfect either with some real-world inaccuracies. The weighting system may not capture nuances in how different factors interact or the varying degrees of vulnerability within neighborhoods. Plus, the

[2] Each pin represents a distinct gas station in Memphis which could potentially become an oasis

model assumes that all criteria are independent of each other, which may not fully reflect real-world interactions (e.g., income and housing quality are often correlated). Finally, Even with well-calculated vulnerability scores, practical constraints such as funding availability, political will, and logistical challenges could hinder the effective allocation of resources as recommended by the model.

If we had more time to work on this project we could find more data on more local neighborhoods to expand on the AHP values and find more neighborhoods in need and more funds that may not be necessary to allocate in the event of a heatwave

4 Conclusion

Our analysis provides a data-driven approach to understanding energy demand trends and heatwave vulnerability in Memphis. First, our results demonstrate the threatening interior temperatures created by abnormal high temperatures during a heat wave. The findings suggest that while overall energy consumption is decreasing due to technological advancements, peak summer demand remains high, requiring continued infrastructure preparedness. The vulnerability model highlights significant disparities in neighborhood resilience, emphasizing the need for equitable resource distribution to mitigate heat-related risks. Moving forward, policymakers should consider refining these models by incorporating additional variables such as climate projections, economic shifts, and evolving energy consumption behaviors to enhance long-term planning and decision-making.

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Appendix A

Neighborhood	ZIP code	Number of hous	Population	Households with	Households with	Population with	Median househo
Coro Lake / Whi	38109	16706	1.177827093	2.383500904	0.781295093	-0.4742300896	-1.011622634
East Memphis –	38111	17866	1.070058612	1.164613733	0.3715499799	0.7285082898	-0.6020523606
Frayser	38127	14183	0.8886005286	0.6456754538	1.136305216	-0.7480429517	-0.9901016155
Egypt / Raleigh	38128	16131	1.182061343	0.5060563454	1.491315339	-0.5161480699	-0.8508084995
South Memphis	38106	9126	-0.3203460224	0.2311426143	-0.6991073508	-0.9126383238	-1.195248016
Bartlett, Zipcode	38134	14698	0.8506971654	0.375703992	0.8784880662	-0.1508078747	-0.386171255
Collierville / Pipe	38017	19969	2.037379759	1.862709274	2.378840647	3.119371441	1.543340315
East Midtown / C	38104	12946	-0.2917306905	-0.09628272828	-0.6914342213	0.5304554471	-0.5079688666
Cordova, Zipcod	38016	18365	1.221194004	1.006461114	0.838587793	1.163263122	-0.01079204826
Lakeland / Arling	38002	15152	1.181173516	1.006461114	1.579300557	1.316321435	1.015172197
Hollywood / Hyd	38108	6569	-0.5441466013	-0.4570683888	-0.5006290688	-1.031854598	-1.050303698
Windyke / South	38125	15549	1.115884119	-0.00855744780	1.007396641	0.6779375154	0.1818391319
Cordova, Zipcod	38018	14215	0.7924420864	0.3126900582	0.6656866091	1.017511613	0.3480980327
East Memphis	38117	11393	-0.00919697221	0.4733138111	-0.06377223151	0.9217540246	0.4528904269
North Memphis /	38107	6659	-0.8462807975	-0.811058429	-0.866893115	-0.7976523045	-1.025582911
Midtown / Evergr	38112	6554	-0.7707472485	-0.6010119828	-0.7773732713	-0.5228780209	-0.6063617252
Bartlett, Zipcode	38135	10925	0.2657560734	0.2669740669	0.1239636693	0.3070210751	0.421150795
South Riverdale	38141	8030	-0.1792498991	-0.8987837095	0.07843643448	-0.8093816476	-0.3119056774
Germantown, Zi	38138	10232	-0.08343292866	1.101599799	0.01756294076	1.081926858	1.393131862
Bartlett, Zipcode	38133	8047	-0.3751180896	-0.7214797976	-0.1297611449	-0.3923169722	0.1638017314
Uptown / Pinch [	38105	3241	-1.463661705	-1.372005997	-1.393269796	-1.092039588	-1.208201915
South Forum / W	38126	2698	-1.429856002	-1.391775074	-1.103225502	-1.177029255	-1.169262806
Oakland	38060	4903	-0.9583518228	-0.7696669235	-0.838246765	-0.7484275203	0.2100435365
Downtown / Sou	38103	8020	-0.9955039482	-1.249684831	-1.288915235	0.09839259525	-0.00965664679
Germantown, Zi	38139	5780	-0.6894086798	-0.4051745609	-0.4418017429	0.3058673693	2.526649592
Rossville	38066	1450	-1.549371112	-1.393628425	-1.442377824	-1.080887098	0.7520687126
Hickory Withe	38028	2709	-1.27667178	-1.160723984	-1.111921716	-0.8139964711	1.927854342

Neighborhood	Population age	Primary mode of	Primary mode of	Primary mode of	Homes built 201	Homes built 199	Homes built 197
Coro Lake / Whi	15010	0.4444591377	0.1816343014	1168	-0.5896662145	2316	0.4680320507
East Memphis –	20766	1.039258911	3.474743158	2364	-0.0282697507	1142	-0.1333897451
Frayser	13659	0.2420420382	0.5054171866	1039	-0.6144972119	1860	0.7503993778
Egypt / Raleigh	18787	1.022497243	-0.1224057249	1401	-0.5162528307	3564	2.126785517
South Memphis	6959	-0.7128941521	0.4935714713	288	-0.827180103	713	-0.9347358529
Bartlett, Zipcode	19285	1.06863174	-0.5212114737	1711	-0.4104511895	2545	2.41533607
Collierville / Pipe	27671	1.832804181	-0.6199257679	5335	3.363860421	10798	0.6473456088
East Midtown / C	13642	0.07410608498	2.104588754	1633	-0.5464818711	1184	-0.501497808
Cordova, Zipcod	23867	1.667262751	-0.3593200311	2502	1.952812001	11843	0.8019262623
Lakeland / Arling	21595	1.242793455	-0.6199257679	2955	1.904229615	9157	-0.2545809775
Hollywood / Hyd	6027	-0.8319818147	-0.1421485837	263	-0.923265267	683	-0.9611176178
Windyke / South	21964	1.378642786	-0.5251600455	2449	1.147423997	9561	0.5092535583
Cordova, Zipcod	19883	1.032713879	-0.4856743278	2525	0.2653837842	9181	0.5871622077
East Memphis	13746	0.1963864464	-0.6120286244	1659	-0.5346061767	745	-0.4025661898
North Memphis /	6009	-0.9272838718	0.8094572129	601	-0.3435154573	1007	-0.9207205403
Midtown / Evergr	7374	-0.8153797813	1.433331553	1107	-0.8261004944	740	-0.8931021302
Bartlett, Zipcode	15371	0.5621100859	-0.5212114737	970	-0.3834609749	5679	0.3781691642
South Riverdale	10421	-0.2333508028	-0.687051488	1045	-0.9405390043	1872	1.163851099
Germantown, Zi	11679	-0.2046165142	-0.5685943349	2093	0.00843694115	2022	1.46847804
Bartlett, Zipcode	10218	-0.245323423	-0.8134057847	949	0.3096477361	3533	-0.02786268569
Uptown / Pinch [	2675	-1.381764536	0.7462800646	130	-0.3564707603	550	-0.9598809725
South Forum / W	1778	-1.486165785	-0.1934800167	125	-0.08440939708	654	-1.157744209
Oakland	5977	-0.9196213949	-0.7107429187	906	0.3355583422	3066	-1.050980504
Downtown / Sou	8563	-0.5695419791	0.3356286005	1034	0.4867035439	4573	-0.9771940057
Germantown, Zi	7201	-0.7623809824	-0.876582933	1187	-0.4935810505	2230	-0.00766414696
Rossville	1740	-1.486165785	-0.8647372177	257	-0.6468854694	642	-1.10662954
Hickory Withe	3435	-1.227237918	-0.8410457871	324	-0.7084231587	1708	-1.02707203

Neighborhood	Homes built 195	Homes built 195	Detached whole	Townhouse	Apartments	Mobile Homes/C	Maximum annua	AHP Score
Coro Lake / Whi	2.256510379	0.5231354172	1.818263561	409	1812	213	102	2.782739055
East Memphis –	2.235433282	2.297969581	1.066345791	985	5757	330	102	2.242995109
Frayser	2.038929888	0.07378373317	1.15521875	295	3523	324	102	2.070867369
Egypt / Raleigh	0.840778001	-0.2469567796	0.7703944595	384	5907	437	102	1.757415879
South Memphis	1.024310875	1.454910229	0.1817752797	682	1853	124	102	0.9756716795
Bartlett, Zipcode	0.226623827	-0.5556235906	0.2183313983	752	5758	37	102	0.8767937271
Collierville / Pipe	-0.5220995035	-0.5482743809	1.922459444	691	3130	106	102	0.7355064008
East Midtown / C	0.2840183829	3.127380399	-0.5526305768	823	7837	39	102	0.511622048
Cordova, Zipcod	-0.6605598162	-0.7152064317	0.8509492598	1428	6642	120	102	0.4970329017
Lakeland / Arling	-0.5824124266	-0.5666474053	1.288528189	84	971	366	102	0.3180753143
Hollywood / Hyd	0.4185875393	0.5635560711	-0.4261070045	500	1082	105	102	0.2245697538
Windyke / South	-0.7532990421	-0.5886950347	0.5123126398	147	5727	80	102	0.1527953237
Cordova, Zipcod	-0.78734666	-0.6999830686	0.8244624912	387	2801	15	102	0.0753290764
East Memphis	1.790220146	-0.4039149029	0.4015497893	611	1403	56	102	-0.01309662882
North Memphis /	-0.1997820542	1.172490596	-0.6250861174	500	2250	52	102	-0.07527081364
Midtown / Evergr	-0.221183414	1.196113056	-0.7535797799	636	1998	93	102	-0.1266843305
Bartlett, Zipcode	-0.6518047145	-0.5697970667	0.4648115755	262	608	32	102	-0.1721028342
South Riverdale	-0.7143874788	-0.7010329557	-0.2448587037	995	233	56	102	-0.2544263029
Germantown, Zi	-0.5139929278	-0.6721610601	-0.02508419407	519	2184	6	102	-0.5155874691
Bartlett, Zipcode	-0.7208727393	-0.6369898419	-0.2871061941	116	1012	379	102	-0.7757207563
Uptown / Pinch [	-0.4053648136	-0.2711041832	-1.585176754	175	3029	15	102	-1.005888846
South Forum / W	-0.5292332901	-0.470057791	-1.542929264	235	1933	0	102	-1.088127741
Oakland	-0.7896165011	-0.6763606086	-0.730376495	52	11	257	102	-1.286871555
Downtown / Sou	-0.6213239899	0.02811364378	-1.453837406	408	6878	26	102	-1.56032771
Germantown, Zi	-0.8207457518	-0.7078572219	-0.5351186637	167	32	0	102	-1.912157699
Rossville	-0.8181516476	-0.7167812624	-1.516880293	34	20	225	102	-2.124292456
Hickory Withe	-0.8032355483	-0.690009141	-1.196631182	50	0	65	102	-2.310858494

Appendix B: AHP Python

```
import pandas as pd
import numpy as np
import os
from scipy.stats import zscore

# === CONFIGURATION ===
csv_file = "your_data.csv"  # Ensure this file exists

columns = [
    "Neighborhood", "ZIP code", "Number of households", "Population",
    "Households with one or more people 65 years and over",
    "Households with one or more people under 18 years",
    "Population with Bachelor's degree or higher",
    "Median household income (in US dollars)",
    "Population age 16+ years old who work",
    "Primary mode of transportation to work (persons aged 16 years+): driving",
    "Primary mode of transportation to work (persons aged 16 years+): walking or public transit",
    "Primary mode of transportation to work (persons aged 16 years+):  other and work from home",
    "Homes built 2010 or later", "Homes built 1990 to 2009", "Homes built 1970 to 1989",
    "Homes built 1950 to 1969", "Homes built 1950 or earlier", "Detached whole house",
    "Townhouse", "Apartments", "Mobile Homes/Other",
    "Maximum annual recorded temperature"
]

weights = {
    "Population": 0.40,
    "Households with one or more people 65 years and over": 0.30,
    "Households with one or more people under 18 years": 0.25,
    "Population with Bachelor's degree or higher": -0.15,
    "Median household income (in US dollars)": -0.40,
    "Primary mode of transportation to work (persons aged 16 years+): driving": -0.15,
    "Primary mode of transportation to work (persons aged 16 years+): walking or public transit": 0.10,
    "Homes built 2010 or later": -0.05,
    "Homes built 1970 to 1989": 0.10,
    "Homes built 1950 to 1969": 0.15,
    "Homes built 1950 or earlier": 0.20,
    "Detached whole house": 0.25,
}  # Adjust weights based on importance

# === STEP 1: VERIFY CSV FILE EXISTS ===
if not os.path.exists(csv_file):
    print(f"Error: File not found at {os.path.abspath(csv_file)}")
    exit()

# === STEP 2: LOAD DATA ===
df = pd.read_csv(csv_file)

# === STEP 3: CLEAN COLUMN NAMES ===
df.columns = df.columns.str.strip()
df.columns = df.columns.str.replace("\\s+", " ", regex=True)

# === STEP 4: CHECK MISSING COLUMNS ===
missing_cols = [col for col in weights.keys() if col not in df.columns]
if missing_cols:
    print(f"Error: These columns are missing from the dataset: {missing_cols}")
    exit()

# === STEP 5: NORMALIZE DATA (ONLY NUMERICAL COLUMNS) ===
numerical_columns = list(weights.keys())
df[numerical_columns] = df[numerical_columns].apply(zscore)

# === STEP 6: APPLY WEIGHTS & COMPUTE SCORES ===
df["AHP Score"] = df[numerical_columns].mul(weights.values(), axis=1).sum(axis=1)

# === STEP 7: RANK NEIGHBORHOODS ===
df = df.sort_values(by="AHP Score", ascending=False)

# === STEP 8: OUTPUT RESULTS ===
output_file = "ranked_neighborhoods.csv"
df.to_csv(output_file, index=False)
print(f"Ranking complete! Results saved in {output_file}")
```

Appendix C

Q1: Power Hungry

Script to code for the triple exponential smoothing equation in google co-lab

```
import numpy as np
import pandas as pd
```

```
from statsmodels.tsa.holtwinters import ExponentialSmoothing
from statsmodels.tsa.stattools import adfuller

def load_dataset():
data = [
608410498.4, 547209444.3, 582730053.8, 662171421.7, 751932974.9, 746892885.5,
669371546.2,
595690279.3, 531609170.8, 550809502.7, 607210473.9, 690011909, 604644382.1,
543822168,
579122901.7, 658072520.4, 747278441.3, 742269550.6, 665228075.4, 592002902.2,
528318461.6,
547399941.7, 603451785.8, 685740672.5, 594136434.9, 534371233.3, 569058485.3,
646636060.4,
734291696.4, 729369853.8, 653667261.1, 581714647.9, 519136961.5, 537886829.9,
592964564.5,
673823375.4, 591953222.8, 532407634.2, 566967424.5, 644259933.3, 731593470.2,
726689713.3,
651265297.1, 579577080.8, 517229342.3, 535910312.4, 590785658.5, 671347345.9,
586765962.8,
527742169.6, 561999114, 638614311.9, 725182548.9, 720321763.4, 645558288,
574498272.4,
512696884.4, 531214154, 585608629.8, 665464358.7, 569940824.2, 512609500.5,
545884148.9,
620302455.1, 704388403.2, 699666997.6, 627047317.1, 558024902, 497995629.2,
515981927.9,
568816677, 646382593.9, 594712778.6, 534889601.5, 569610502, 647263331.5,
735003998.1,
730077381, 654301352.8, 582278941.8, 519640551.8, 538408608.5, 593539771.4,
674477019.6,
571947963.2, 514414737.9, 547806568.4, 622486950.7, 706869021.1, 702130988.4,
629255565.9,
559990077.1, 499749401.5, 517799041.9, 570819857.1, 648658935, 533416309.2,
479759049,
510901299.9, 580550527.6, 659247848.7, 654829013.3, 586863146.8, 522264015.9,
466081704,
482915355.3, 532364202.7, 599530693.5, 538816255.7, 484615805.6, 516073319.7,
586427629.1,
```

```
665921628.8, 661458060, 592804153, 527551064.1, 470800000.4, 487804064.3,
537753498.4,
611083527, 536254849, 482312053.5, 513620028.9, 583639892.8, 662755992.8,
658313644.9,
589986104, 525043209.1, 468561929.2, 485485159.1, 535197147.1, 608178576.2
]
return np.array(data)
def check_stationarity(data):
result = adfuller(data)
print("ADF Statistic:", result[0])
print("p-value:", result[1])
if result[1] > 0.05:
print("Data is likely non-stationary.")
else:
print("Data is likely stationary.")

def triple_exponential_smoothing(data, season_length, forecast_periods):
model = ExponentialSmoothing(
data,
trend='add',
seasonal='mul',
seasonal_periods=season_length
)
fit = model.fit(optimized=True)
level = fit.level
trend = fit.trend
seasonal = fit.season
print("\nEquation for Triple Exponential Smoothing:")
print(f"y_t = ({level[-1]:.4f} + t * {trend[-1]:.4f}) * S_{season_length}(t)")
forecast = fit.forecast(forecast_periods)
return fit.fittedvalues, forecast

def main():
season_length = 12
forecast_periods = 120
data = load_dataset()
check_stationarity(data)
```

```
fitted_values, forecast = triple_exponential_smoothing(data, season_length,
forecast_periods)
print("\nFitted Values (Original Scale):")
print(fitted_values)
print("\nForecast (Original Scale):")
print(forecast)
if __name__ == "__main__":
main()
```

Appendix D

Q2: Power Hungry

Script to code for seasonal factors in google co-lab

```
import pandas as pd
import numpy as np
from statsmodels.tsa.seasonal import seasonal_decompose

dates = pd.date_range(start="2012-01", periods=132, freq='ME')
values = [
608410498.4, 547209444.3, 582730053.8, 662171421.7, 751932974.9, 746892885.5,
669371546.2, 595690279.3, 531609170.8, 550809502.7, 607210473.9, 690011909,
604644382.1, 543822168, 579122901.7, 658072520.4, 747278441.3, 742269550.6,
665228075.4, 592002902.2, 528318461.6, 547399941.7, 603451785.8, 685740672.5,
594136434.9, 534371233.3, 569058485.3, 646636060.4, 734291696.4, 729369853.8,
653667261.1, 581714647.9, 519136961.5, 537886829.9, 592964564.5, 673823375.4,
591953222.8, 532407634.2, 566967424.5, 644259933.3, 731593470.2, 726689713.3,
651265297.1, 579577080.8, 517229342.3, 535910312.4, 590785658.5, 671347345.9,
586765962.8, 527742169.6, 561999114, 638614311.9, 725182548.9, 720321763.4,
645558288, 574498272.4, 512696884.4, 531214154, 585608629.8, 665464358.7,
569940824.2, 512609500.5, 545884148.9, 620302455.1, 704388403.2, 699666997.6,
627047317.1, 558024902, 497995629.2, 515981927.9, 568816677, 646382593.9,
594712778.6, 534889601.5, 569610502, 647263331.5, 735003998.1, 730077381,
654301352.8, 582278941.8, 519640551.8, 538408608.5, 593539771.4, 674477019.6,
571947963.2, 514414737.9, 547806568.4, 622486950.7, 706869021.1, 702130988.4,
629255565.9, 559990077.1, 499749401.5, 517799041.9, 570819857.1, 648658935,
533416309.2, 479759049, 510901299.9, 580550527.6, 659247848.7, 654829013.3,
586863146.8, 522264015.9, 466081704, 482915355.3, 532364202.7, 599530693.5,
538816255.7, 484615805.6, 516073319.7, 586427629.1, 665921628.8, 661458060,
592804153, 527551064.1, 470800000.4, 487804064.3, 537753498.4, 611083527,
```

```
536254849, 482312053.5, 513620028.9, 583639892.8, 662755992.8, 658313644.9,
589986104, 525043209.1, 468561929.2, 485485159.1, 535197147.1, 608178576.2
]

assert len(dates) == len(values),
df = pd.DataFrame({"Date": dates, "Value": values}).set_index("Date")

decomposition = seasonal_decompose(df["Value"], model="additive", period=12)
seasonal_values = decomposition.seasonal[:12]

seasonal_values_rounded = [f"{val:.10g}" for val in seasonal_values]

seasonality_dict = dict(zip(dates[:12].strftime("%b"),
seasonal_values_rounded))
print(seasonality_dict)
```

Appendix E - data for monthly Energy use in memphis and calculations

	A	B	C	D	E	F	G	H
46	year	E use year shelby	month to total ratio	E use month shelby	month	Population	E use/capita shelby	Month E use memphis
47	2022.00	9768296000.00	0.091464385	893451181.9	Jan		974.9576406	608178576.2
48			0.080488658	786237040.1	feb	shelby2022	857.9627238	535197147.1
49			0.073012439	713207117.4	march	916400.00	778.270534	485485159.1
50			0.070467343	688345867.1	april		751.1412779	468561929.2
51			0.078961601	771320289.9	may	memphis 2022	841.6851701	525043209.1
52			0.088728406	866725337.8	june	623800	945.7936903	589986104
53			0.099004231	967102635.8	july		1055.328062	658313644.9
54			0.099672319	973628714	august		1062.449492	662755992.8
55			0.087773995	857402369	september		935.6202193	583639892.8
56			0.077243661	754538945.9	october		823.3729222	513620028.9
57			0.072535234	708545632.9	november		773.1837985	482312053.5
58			0.080647727	787790868.2	december		859.6583023	536254849
59	2021	9800375000	0.091464385	896385272.1	Jan		970.7442843	611083527
60			0.080488658	788819031.6	feb	shelby21	854.2549617	537753498.4
61			0.073012439	715549281.9	march	923400.00	774.9071712	487804064.3
62			0.070467343	690606386.7	april		747.8951556	470800000.4
63			0.078961601	773853300.4	may	memphis 21	838.0477587	527551064.1
64			0.088728406	869571652	june	629500	941.7063591	592804153
65			0.099004231	970278590.4	july		1050.767371	661458060
66			0.099672319	976826103.3	august		1057.858028	665921628.8
67			0.087773995	860218066.2	september		931.5768532	586427629.1
68			0.077243661	757016844.2	october		819.8146461	516073319.7
69			0.072535234	710872493.9	november		769.8424236	484615805.6
70			0.080647727	790377967.5	december		855.943218	538816255.7
71	2020	9672364000.00	0.091464385	884676824.8	Jan		952.391888	599530693.5
72			0.080488658	778515598	feb	shelby20	838.1048531	532364202.7
73			0.073012439	706202886.5	march	928900.00	760.2571714	482915355.3
74			0.070467343	681585791.6	april		733.7558312	466081704
75			0.078961601	763745346.9	may	memphis 20	822.2040552	522264015.9
76			0.088728406	858213440	june	635200	923.9029389	586863146.8
77			0.099004231	957604959.8	july		1030.902099	654829013.3
78			0.099672319	964066950.1	august		1037.858704	659247848.7
79			0.087773995	848982029.4	september		913.9649363	580550527.6
80			0.077243661	747128805.9	october		804.3156485	510901299.9
81			0.072535234	701587186.1	november		755.2881753	479759049
82			0.080647727	780054171.3	december		839.7611921	533416309.2
83	2019	10208674000.00	0.091464385	933730089.1	Jan		996.403894	648658935
84			0.080488658	821682470.2	feb	shelby19	876.835418	570819857.1
85			0.073012439	745360187.7	march	937100	795.3902334	517799041.9
86			0.070467343	719378132.3	april		767.6642112	499749401.5
87			0.078961601	806093243.1	may	memphis 19	860.1998113	559990077.1
88			0.088728406	905799371.4	june	651000	966.5984115	629255565.9
89			0.099004231	1010701919	july		1078.542225	702130988.4
90			0.099672319	1017522211	august		1085.820309	706869021.1
91			0.087773995	896056100.6	september		956.2011532	622486950.7
92			0.077243661	788555353.7	october		841.4847441	547806568.4
93			0.072535234	740488557.4	november		790.1916097	514414737.9
94			0.080647727	823306353.8	december		878.5682998	571947963.2
95	2018	10604732000.00	0.091464385	969955290.5	Jan		1034.950161	674477019.6
96			0.080488658	853560647.1	feb	shelby18	910.7561322	593539771.4
97			0.073012439	774277348.3	march	937200.00	826.1602094	538408608.5
98			0.070467343	747287287.3	april		797.3615955	519640551.8

	A	B	C	D	E	F	G	H
100			0.088728406	940940966.4	june	651700	1003.991642	654301352.8
101			0.099004231	1049913337	july		1120.266044	730077381
102			0.099672319	1056998231	august		1127.825684	735003998.1
103			0.087773995	930819693.5	september		993.1921613	647263331.5
104			0.077243661	819148323.6	october		874.037904	569610502
105			0.072535234	769216717.1	november		820.760475	534889601.5
106			0.080647727	855247531.2	december		912.5560513	594712778.6
107	2017	10154668000.00	0.091464385	928790463.5	Jan	shelby17	992.2975037	646382593.9
108			0.080488658	817335599.8	feb	936000.00	873.2217946	568816677
109			0.073012439	741417077.9	march		792.1122627	515981927.9
110			0.070467343	715572473	april	memphis 17	764.5005053	497995629.2
111			0.078961601	801828842.9	may	651400	856.6547467	558024902
112			0.088728406	901007505.1	june		962.6148559	627047317.1
113			0.099004231	1005355096	july		1074.097325	699666997.6
114			0.099672319	1012139308	august		1081.345415	704388403.2
115			0.087773995	891315778.3	september		952.2604469	620302455.1
116			0.077243661	784383732.6	october		838.0168083	545884148.9
117			0.072535234	736571219.6	november		786.9350636	512609500.5
118			0.080647727	818950892.6	december		874.9475349	569940824.2
119	2016	10436626000.00	0.091464385	954579578.6	Jan		1019.087839	665464358.7
120			0.080488658	840030020.8	feb	shelby16	896.7972892	585608629.8
121			0.073012439	762003519.2	march	936700.00	813.4979387	531214154
122			0.070467343	735441304.1	april		785.1407111	512696884.4
123			0.078961601	824092698	may	memphis 16	879.7829593	574498272.4
124			0.088728406	926025189	june	653000	988.6038102	645558288
125			0.099004231	1033270131	july		1103.096115	720321763.4
126			0.099672319	1040242716	august		1110.539891	725182548.9
127			0.087773995	916064358.3	september		977.9698498	638614311.9
128			0.077243661	806163200.7	october		860.6418285	561999114
129			0.072535234	757023109.1	november		808.1809641	527742169.6
130			0.080647727	841690164.4	december		898.5696215	586765962.8
131	2015	10514853000.00	0.091464385	961734563	Jan		1025.740788	671347345.9
132			0.080488658	846326407	feb	shelby15	902.6518846	590785658.5
133			0.073012439	767715063.3	march	937600.00	818.8087279	535910312.4
134			0.070467343	740953752.9	april		790.2663747	517229342.3
135			0.078961601	830269627.2	may	memphis 15	885.5264795	579577080.8
136			0.088728406	932966146	june	654500	995.0577496	651265297.1
137			0.099004231	1041014935	july		1110.297499	726689713.3
138			0.099672319	1048039782	august		1117.78987	731593470.2
139			0.087773995	922930654.6	september		984.3543672	644259933.3
140			0.077243661	812205740.6	october		866.2603889	566967424.5
141			0.072535234	762697322.8	november		813.4570423	532407634.2
142			0.080647727	847998994.2	december		904.4357873	591953222.8
143	2014	10544122000.00	0.091464385	964411634.1	Jan		1028.267016	673823375.4
144			0.080488658	848682229.6	feb	shelby14	904.8749649	592964564.5
145			0.073012439	769852064.3	march	937900.00	820.8253165	537886829.9
146			0.070467343	743016261.6	april		792.2126683	519136961.5
147			0.078961601	832580754.3	may	memphis 14	887.7073827	581714647.9
148			0.088728406	935563137.7	june	655300	997.50841	653667261.1
149			0.099004231	1043912690	july		1113.031976	729369853.8
150			0.099672319	1050957092	august		1120.542799	734291696.4
151			0.087773995	925499711.7	september		986.7786669	646636060.4
152			0.077243661	814466585.3	october		868.393843	569058485.3

	A	B	C	D	E	F	G	H
153			0.072535234	764820356.6	november		815.4604506	534371233.3
154			0.080647727	850359472.5	december		906.663261	594136434.9
155	2013	10705452000.00	0.091464385	979167583.3	Jan		1043.110241	685740672.5
156			0.080488658	861667464.8	feb	shelby13	917.9370031	603451785.8
157			0.073012439	781631161.1	march	938700.00	832.6740824	547399941.7
158			0.070467343	754384758.1	april		803.6484053	528318461.6
159			0.078961601	845319629.3	may	memphis 13	900.5216037	592002902.2
160			0.088728406	949877691.5	june	657400	1011.907629	665228075.4
161			0.099004231	1059885043	july		1129.098799	742269550.6
162			0.099672319	1067037227	august		1136.718043	747278441.3
163			0.087773995	939660290.3	september		1001.023	658072520.4
164			0.077243661	826928305.1	october		880.9292694	579122901.7
165			0.072535234	776522465.9	november		827.2317736	543822168
166			0.080647727	863370370.3	december		919.7511136	604644382.1
167	2012	10753992000.00	0.091464385	983607264.6	Jan		1047.059043	690011909
168			0.080488658	865574384.2	feb	shelby12	921.4119483	607210473.9
169			0.073012439	785175184.9	march	939400	835.826256	550809502.7
170			0.070467343	757805242.9	april		806.6906993	531609170.8
171			0.078961601	849152425.5	may	memphis 12	903.9306211	595690279.3
172			0.088728406	954184568.3	june	659000	1015.73831	669371546.2
173			0.099004231	1064690708	july		1133.373119	746892885.5
174			0.099672319	1071875321	august		1141.021206	751932974.9
175			0.087773995	943920840	september		1004.812476	662171421.7
176			0.077243661	830677712.4	october		884.264118	582730053.8
177			0.072535234	780043326.2	november		830.3633449	547209444.3
178			0.080647727	867285011	december		923.2329263	608410498.4

Appendix F - calculations for ratio of month per year

32	energy consumption SEUs a	total per year	Month	consumption per month	ratio of month per year
33	28750000000.00	314330000000.00	January	28750000000.00	0.091464385
34	25300000000.00		Feburary	25300000000.00	0.080488658
35	22950000000.00		March	22950000000.00	0.073012439
36	22150000000.00		April	22150000000.00	0.070467343
37	24820000000.00		May	24820000000.00	0.078961601
38	27890000000.00		June	27890000000.00	0.088728406
39	31120000000.00		July	31120000000.00	0.099004231
40	31330000000.00		August	31330000000.00	0.099672319
41	27590000000.00		September	27590000000.00	0.087773995
42	24280000000.00		October	24280000000.00	0.077243661
43	22800000000.00		November	22800000000.00	0.072535234
44	25350000000.00		December	25350000000.00	0.080647727

Appendix G - calculations for per month capita in shelby county

	South East USA			
Month	**Consumption (kWh)**			
January	28750000000.00			
Feburary	25300000000.00			
March	22950000000.00			
April	22150000000.00			
May	24820000000.00			
June	27890000000.00			
July	31120000000.00			
August	31330000000.00			
September	27590000000.00			
October	24280000000.00			
November	22800000000.00			
December	25350000000.00			
	Consumption shelby county			
	(kWh)	average per month	avergage per month per capita	population of shelby
2022.00	9768296000.00	814024666.7	888.2853194	916400.00
2021.00	9800375000.00	816697916.7	884.4465201	923400.00
2020.00	9672364000.00	806030333.3	867.7256253	928900.00
2019.00	10208674000.00	850722833.3	907.8250276	937100.00
2018.00	10604732000.00	883727666.7	942.9445867	937200.00
2017.00	10154668000.00	846222333.3	904.0836895	936000.00
2016.00	10436626000.00	869718833.3	928.4924024	936700.00
2015.00	10514853000.00	876237750	934.5539142	937600.00
2014.00	10544122000.00	878676833.3	936.8555638	937900.00
2013.00	10705452000.00	892121000	950.3792479	938700.00
2012.00	10753992000.00	896166000	953.9770066	939400.00