# M3 Challenge 2025

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

Team: #18375

March 1st, 2025

# Executive Summary

To the Secretary of the U.S. Department of Energy,

As global temperatures rise due to climate change, the frequency and intensity of heat waves have increased, leading to significant risks of public health and infrastructure. Vulnerable populations, including low-income households and the elderly, are immensely affected by extreme heat events, as they may lack access to air conditioning or live in poorly insulated homes. Additionally, increased energy consumption during heat waves burdens power grids, increasing the concerns about energy sustainability and solidity. Addressing these issues requires a comprehensive understanding of indoor temperature variations, electricity demand, and community vulnerability to extreme heat.

We first developed a mathematical model to predict the indoor temperature of non-air-conditioned dwellings during a heat wave over a 24-hour period. We selected Memphis, Tennessee, as our case study location. Our model accounts for outdoor weather conditions, including temperature, wind speed, and solar radiation, as well as building characteristics such as insulation and shading. Utilizing Newton's Law of Cooling and heat balance equations, we estimated indoor temperature fluctuations. The model predicts that poorly insulated homes experience temperature increases of up to 2°C above peak outdoor temperature, while the temperature of a well-insulated home remains constantly 2°C lower than peak outdoor temperature.

Next, we analyzed electricity demand in Memphis during summer months to forecast peak energy consumption over the next 20 years. Using historical energy consumption data and an exponential growth model, we estimated that peak electricity demand will increase by approximately 2.3% by 2045. Our model suggests that increasing adoption of energy-efficient appliances and improvements in building insulation could diminish demand growth, while higher electric vehicle ownership could intensify it. The results indicate the requirement for infrastructure planning to encompass future energy demands and prevent grid failures during extreme heat events.

Finally, we developed a vulnerability score to assess the susceptibility of different neighborhoods in Memphis to heat-related risks. Our vulnerability model includes four key factors: median household income, percentage of elderly residents, age of housing stock, and reliance on public transportation. By normalizing these factors and computing a weighted vulnerability index, we identified high-risk areas where targeted interventions, such as cooling centers and energy assistance programs, would be most beneficial. Our analysis highlights that neighborhoods with lower incomes and older housing structures exhibit the highest vulnerability to extreme heat.

We believe these results will assist policymakers in developing effective heat mitigation strategies, improving energy resilience, and protecting vulnerable communities from the adverse effects of extreme heat. Our findings emphasize the importance of enhancing building insulation, promoting energy-efficient technologies, and implementing targeted public health interventions to safeguard residents from the growing risks associated with rising temperatures.

# Table of Contents

# 1. Hot to Go

## 1.1 Defining the problem

The first problem asks us to develop a model to predict the indoor temperature of any non-air-conditioned dwelling during a heat wave over 24 hours. We have selected Memphis, Tennessee as our city. Our model will utilize weather conditions such as outdoor temperature, dewpoints, and wind speed, as well as the house conditions such as dwelling type and number of stories to estimate the closest indoor temperature variations within one day (24hrs).

## 1.2 Assumptions

**1.2-1** The initial indoor temperature is 25.5 degrees Celsius

- Justification: The MLGW site recommends setting the thermostat to 78 Fahrenheit during the summer, so we will assume that the *initial* temperature is 25.5 Celsius (equivalent to 78 Fahrenheit).

**1.2-2** The houses 1 and 2 will have a minimum R-value of R-7, while houses 3 and 4 will have the moderate R-value of R-20.

- Justification: Tennessee is located in the Climate zone 3, which requires a minimum insulation R-value of R-20. However, the houses built during the 1950s-60s do not have high insulation capability. Therefore, based on the minimum R-value according to the Climate zone and the year of structures built, the R-value of House 1 and 2 will be R-7 and R-20 for House 3 and 4.

**1.2-3** Windows are closed throughout the day.

- Justification: This assumption is made to simplify the problem, as accounting for varying airflow through open windows would introduce additional complexity to the heat transfer calculations.

**1.2-4** The thermal capacity of the house is only dependent on the volume of the air trapped inside the house

- Justification: The indoor temperature is primarily affected by the air volume inside the house. While the insulation and heat capacity of the walls can influence temperature changes, they are accounted for separately using the insulation factor. This assumption simplifies the heat transfer calculations by focusing on air volume as the primary heat-retaining medium.

**1.2-5** Dew point does not affect the actual change of temperature.

- Justification: The outdoor dew point measures moisture content in the air but does not directly alter the indoor temperature. While the dew point may alter the rate of heat transfer, it is negligible as its variations are very small.

**1.2-6** The thermal coefficient of the air is 28W/m^2

- Justification: According to the thermal coefficient of the air in 30 degrees Celsius (which is the temperature most of the heat exchange takes place) is 28W/m^2.

**1.2-7** The temperature inside the house follows temperature balance equation consisting of heat from solar radiation, heat transfer through the walls, and Heat gain from the appliances

- Justification: The indoor temperature is determined by three major sources: heat gain from solar radiation, heat transfer through the walls, and internal heat generation from appliances and human activities. The model accounts for these factors to create a comprehensive heat balance equation.

**1.2-8** Heat transfer through the walls directly follows Newton's Law of Cooling.

- Justification: Newton's Law of Cooling provides a reliable model for heat exchange through walls by describing the rate of heat loss or gain between the indoor and outdoor environments. This simplifies the estimation of temperature changes due to heat conduction.

**1.2-9** The height of the house is 3m.

- Justification: A standard residential house typically has a ceiling height of around 3 meters (9ft). This assumption ensures consistency in calculating the volume of air inside the house, which affects thermal capacity and heat retention.

**1.2-10** Individual human activities and appliances emit 150W of heat.

- Justification: The average metabolic heat output of a resting human is approximately 80W, while household appliances contribute additional heat of around 70W. A total assumption of 105W accounts for combined heat emissions from occupants and household devices.

**1.2-11** Heat gain from solar radiation directly follows NASA's solar radiation chart.

- Justification: Solar radiation is a major factor influencing indoor temperature changes. To ensure accuracy, the heat gain from sunlight is modeled using NASA's solar radiation data, which provides reliable estimates of solar energy absorption based on geographic location and time of day.

**1.2-12** The proportional factor of $p$ in $U(t) = w * p + k$ is 0.1.

- Justification: The coefficient 0.1 is based on empirical studies showing that the convective heat transfer coefficient increases by approximately 0.1–0.2 $J/°C$ per m/s of wind speed. This value provides a reasonable approximation for moderate wind speeds. It aligns with experimental data on forced convection over buildings and is consistent with ASHRAE guidelines for heat transfer modeling.

**1.2-13** Temperature increase on the 15th floor is modeled as 1 degree higher than the base temperature.

- Justification: Higher floors experience greater solar radiation due to reduced shading, leading to increased heat gain. Additionally, heat accumulates more on upper floors due to reduced contact with cooler surfaces, making temperature regulation less effective and justifying the 1-degree increase.

## 1.3 The Model

### 1.3-1 Model Development

Using temperature balance equation, we get that:

$$\frac{dT_{in}}{dt} = \frac{Q_{solar}+Q_{app}+Q_{wall}}{C}$$

| Symbol | Definition | Units |
|---|---|---|
| $T_{in}$ | Indoor temperature | ℃ |
| $Q_{solar}$ | Heat gain from solar radiation | $J$ |
| $Q_{app}$ | Heat gain from appliances and human activities (200 per person) | $J$ |
| $Q_{wall}$ | Heat transfer through walls | $J$ |
| $C$ | Thermal capacity of the building | $J/$℃ |

$$C = M * Sp_{heat}$$

| Symbol | Definition | Units |
|---|---|---|
| $M$ | Mass | g |
| $Sp_{heat}$ | Specific heat of the air (1.005) | $J/g$℃ |

$$M = \rho V$$

| Symbol | Definition | Units |
|---|---|---|

| | | |
|---|---|---|
| ρ | Density of the air (1225.0) | $g/m^3$ |
| $V$ | Volume (Surface Area*height = 3* Surface Area) | $m^3$ |

Thus, we get that

$C = 3 \cdot A \cdot 1225.0 \cdot 1.005$

$C = 3693.375A$

Using Newton's law of cooling, we get that:

$Q_{wall} = (T_{out} - T_{in}) \cdot U(t)$

Where the variables are

| Symbol | Definition | Units |
|---|---|---|
| $T_{out}$ | outside temperature | ℃ |
| $T_{in}$ | inside temperature | ℃ |
| U(t) | Actual coefficient of thermal transfer | $J/$℃ |

We then calculate the actual coefficient of thermal transfer through the equation

$U(t) = (1 - insulation\,factor)(w * p + k)$

| Symbol | Definition | Units |
|---|---|---|
| w | Wind Speed | $m/s$ |
| k | Coefficient of thermal transfer (28) | $J/$℃ |
| p | Proportional factor for convective heat transfer due to wind (0.1) | $Js/m$℃ |
| Insulation factor (R-value) | given through the R score of the material of the house | N/a |

The equation that is used in the actual simulation is:

$\frac{dT}{dt} = (W(t) + U(t) \cdot (T_{out}(t - 1) - T_{in}(t - 1)) + Q)/C$

| Symbol | Definition | Units |
|---|---|---|
| $W(t)$ | Heat gain from solar radiation ($Q_{solar}$) through the wall | $J$ |
| $Q$ | Sum of heat gain from appliances and humans inside the house. | $J$ |
| $C$ | Thermal capacity of the building | $J/°C$) |
| U(t) | Actual coefficient of thermal transfer | $J/°C$ |
| $T_{out}(t)$ | Outside temperature of the house | °C |

$W(t)$ is calculated by:
$W(t) = \varepsilon\sigma A(T^4_{inside} - T^4_{outside})$ where Temperature is in Kelvin instead of Celsius

| Symbol | Definition | Units |
|---|---|---|
| ε | Emissivity of the wall surface | N/a |
| σ | Stefan-Boltzmann constant $5.670 \cdot 10^{-8} W/m^2 \cdot K^4$ | $W/m^2 \cdot K^4$ |
| $A$ | Surface Area | $m^2$ |

## 1.3-2 Model Execution

Because the outside temperature and wind speed are given in discrete intervals, we sum $\frac{dT}{dt}$ throughout 24 hours in order to get the change of temperature over 24 hours.

We will have to estimate the proportion not covered by the shade
- If the house is *not at all shady*, multiply by 1.
- If the house is *very shady*, multiply by 0.1 because some light will still go through.
- If the house is *not very shady*, multiply by 0.7.

The code will be provided in the appendix.

## 1.4 Results

We find tables and graphs for each house in Memphis, Tennessee, as follows using Python:

| Hour int64 0 - 23 | Outdoor Temp (°C) 28.3 - 38.9 | Indoor Temp (°C) f. 25.5 - 37.659095... |
|---|---|---|
| 0 | 29.4 | 25.5 |
| 1 | 29.4 | 26.73566896 |
| 2 | 28.9 | 27.57731344 |
| 3 | 28.3 | 28.00023303 |
| 4 | 28.3 | 28.09615612 |
| 5 | 28.3 | 28.16227915 |
| 6 | 28.9 | 28.20755479 |
| 7 | 31.1 | 28.42885129 |
| 8 | 32.8 | 29.2844668 |
| 9 | 34.4 | 30.41010197 |
| 10 | 35.6 | 31.69183931 |
| 11 | 36.1 | 32.94300337 |
| 12 | 37.8 | 33.93995899 |
| 13 | 37.8 | 35.17570801 |
| 14 | 38.9 | 36.01337714 |
| 15 | 38.9 | 36.95062109 |
| 16 | 37.8 | 37.59047994 |
| 17 | 37.2 | 37.65909569 |
| 18 | 36.1 | 37.51316431 |
| 19 | 34.4 | 37.06421643 |
| 20 | 33.3 | 36.22248921 |
| 21 | 32.8 | 35.29578359 |
| 22 | 32.2 | 34.50181618 |
| 23 | 31.7 | 33.75945867 |

Figure 1 (House 1)

| Hour int64 0 - 23 | Outdoor Temp (°C) 28.3 - 38.9 | Indoor Temp (°C) f. 25.5 - 38.309414... |
|---|---|---|
| 0 | 29.4 | 25.5 |
| 1 | 29.4 | 27.22355105 |
| 2 | 28.9 | 28.18287025 |
| 3 | 28.3 | 28.50358501 |
| 4 | 28.3 | 28.41596536 |
| 5 | 28.3 | 28.36652923 |
| 6 | 28.9 | 28.33888926 |
| 7 | 31.1 | 28.58938136 |
| 8 | 32.8 | 29.7111931 |
| 9 | 34.4 | 31.0908628 |
| 10 | 35.6 | 32.57387544 |
| 11 | 36.1 | 33.92549322 |
| 12 | 37.8 | 34.88380095 |
| 13 | 37.8 | 36.18631821 |
| 14 | 38.9 | 36.90542298 |
| 15 | 38.9 | 37.80921898 |
| 16 | 37.8 | 38.3094146 |
| 17 | 37.2 | 38.08337849 |
| 18 | 36.1 | 37.68998427 |
| 19 | 34.4 | 36.98527761 |
| 20 | 33.3 | 35.84619551 |
| 21 | 32.8 | 34.7203915 |
| 22 | 32.2 | 33.86877466 |
| 23 | 31.7 | 33.11865248 |

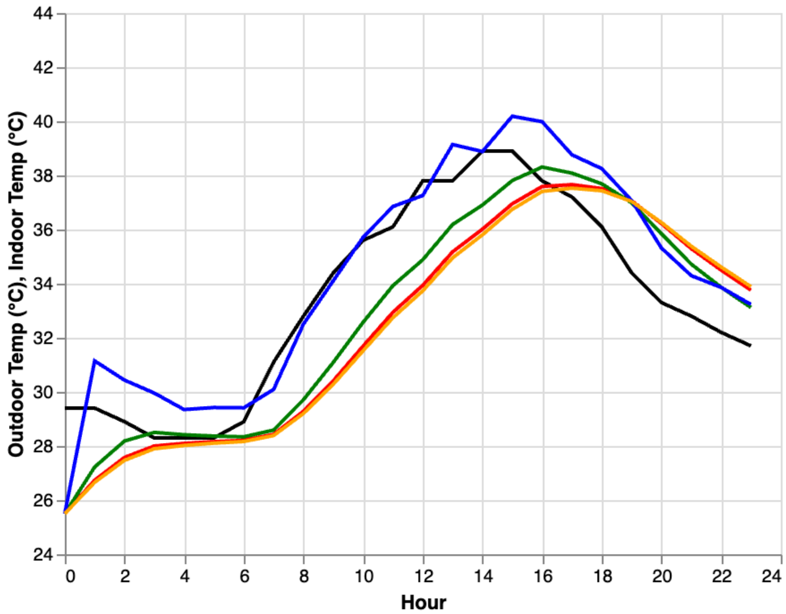
Figure 2 (House 2)

| Hour int64 0 - 23 | Outdoor Temp (°C) 29.41 - 40.01 | Indoor Temp (°C) f. 25.5 - 40.186374... |
|---|---|---|
| 0 | 30.51 | 25.5 |
| 1 | 30.51 | 31.1460093 |
| 2 | 30.01 | 30.43555358 |
| 3 | 29.41 | 29.95622271 |
| 4 | 29.41 | 29.34650381 |
| 5 | 29.41 | 29.42155951 |
| 6 | 30.01 | 29.41174238 |
| 7 | 32.21 | 30.09117212 |
| 8 | 33.91 | 32.50574103 |
| 9 | 35.51 | 34.10699971 |
| 10 | 36.71 | 35.7122804 |
| 11 | 37.21 | 36.85080047 |
| 12 | 38.91 | 37.25710894 |
| 13 | 38.91 | 39.14097116 |
| 14 | 40.01 | 38.88239939 |
| 15 | 40.01 | 40.18637464 |
| 16 | 38.91 | 39.98413414 |
| 17 | 38.31 | 38.76115171 |
| 18 | 37.21 | 38.24937449 |
| 19 | 35.51 | 37.07421594 |
| 20 | 34.41 | 35.31625836 |
| 21 | 33.91 | 34.29550379 |
| 22 | 33.31 | 33.86165276 |
| 23 | 32.81 | 33.23066532 |

Figure 3 (House 3)

| Hour int64 0 - 23 | Outdoor Temp (°C) 28.3 - 38.9 | Indoor Temp (°C) f. 25.5 - 37.528752... |
|---|---|---|
| 0 | 29.4 | 25.5 |
| 1 | 29.4 | 26.65830344 |
| 2 | 28.9 | 27.47041563 |
| 3 | 28.3 | 27.89962947 |
| 4 | 28.3 | 28.02046678 |
| 5 | 28.3 | 28.106214 28. |
| 6 | 28.9 | 28.1666692 |
| 7 | 31.1 | 28.38733992 |
| 8 | 32.8 | 29.20208139 |
| 9 | 34.4 | 30.28164258 |
| 10 | 35.6 | 31.52105857 |
| 11 | 36.1 | 32.74411522 |
| 12 | 37.8 | 33.73657691 |
| 13 | 37.8 | 34.95456765 |
| 14 | 38.9 | 35.80518489 |
| 15 | 38.9 | 36.74625459 |
| 16 | 37.8 | 37.40871168 |
| 17 | 37.2 | 37.52875217 |
| 18 | 36.1 | 37.43273191 |
| 19 | 34.4 | 37.03820923 |
| 20 | 33.3 | 36.26007471 |
| 21 | 32.8 | 35.38344079 |
| 22 | 32.2 | 34.61588144 |
| 23 | 31.7 | 33.88803373 |

Figure 4 (House 4)




Red: House 1; Green: House 2; Blue: House 3; Orange: House 4; Black: Outside Temperature

## 1.5 Discussion

The model effectively predicts indoor temperature in non-air conditioned dwelling in Memphis, Tennessee during a heat wave by considering insulation value, shading, wind speed, and solar exposure. We have excluded the Dew point since it does not affect the temperature itself. The result illustrates that shading significantly reduced the temperature increases, sometimes even more than insulation. Dwellings with a higher insulation value of R-20 heat up slower but houses with more shade (0.1 factor) remain cooler regardless of insulation. Although there are some internal factors affecting the elevation of heat, external heat gain is the factor that dominantly influences the temperature. This finding emphasizes that shading and insulation, as well as other environmental and structural factors collectively influenced the indoor temperature of houses.

## 1.6 Sensitivity Analysis

To evaluate the robustness of our model, we conducted a sensitivity analysis on key parameters:

The initial indoor temperature was varied from 24°C to 27°C. The results showed that within 24 hours, the temperature trend remained consistent, with an average variation of ±1°C from the baseline assumption. Houses with R-7 insulation exhibited up to a 3°C greater temperature increase than those with R-20, emphasizing the importance of insulation in thermal regulation. Wind speeds ranging from 1 m/s to 5 m/s showed a temperature difference of approximately 1°C, confirming the impact of convective cooling. The model was highly sensitive to shading factors, as fully exposed houses (shading factor 1.0) experienced a temperature rise up to 3°C higher than heavily shaded homes (shading factor 0.1). Increasing internal heat sources by 50W per person and appliance raised the predicted temperature by approximately 0.3–0.5°C, indicating a minor but noticeable effect.

This sensitivity analysis suggests that insulation and solar exposure have the most significant impact on indoor temperature changes, while initial temperature and internal heat sources have a relatively smaller influence.

### 1.7 Strength and Weakness

The model effectively captures key heat transfer mechanisms, including solar radiation, heat conduction, and internal heat generation. It provides a practical framework for estimating indoor temperature in non-air-conditioned houses. The use of empirical coefficients and established physics-based equations ensures reliability. The model is adaptable and can be used for different geographic locations by adjusting input parameters.

However, the model assumes that windows remain closed, excluding potential ventilation effects. The analysis is limited to the hottest summer day and does not consider daily variations in weather conditions. It simplifies wall thermal inertia and does not account for heat storage and delayed heat release from structural elements. The assumption that heat transfer follows Newton's Law of Cooling may oversimplify real-world heat exchange dynamics, especially in highly insulated buildings. The impact of humidity and latent heat effects are ignored, which may affect the accuracy in high-humidity conditions. Additionally, the model does not take into account the height of the houses, which can influence the volume of air inside and the overall thermal capacity.

Despite these limitations, the model provides a strong foundation for predicting indoor temperatures during heatwaves, offering insights into passive cooling strategies and the importance of insulation and shading in mitigating extreme heat exposure.

# 2. Power Hungry

## 2.1 Defining the Problem

The second problem requires us to develop a model which can predict the peak demand that Memphis' power grid should be prepared to handle during summer months. Additionally, we must forecast changes in maximum demand 20 years from now. This involves analyzing historical energy consumption, regional consumption trends, and national averages to establish a predictive model.

## 2.2 Assumptions

**2.2-1** There is an exponential growth relationship in electricity consumption during summer annually.

- Justification: We assume that peak power demand follows an exponential growth model, as energy consumption tends to increase at a compounding rate rather than a linear rate due to population growth, increased energy usage, and evolving lifestyle demands.

**2.2-2** Data of electricity consumption from 2012 to 2024 is sufficient to predict the peak power demand of 2045.

- Justification: A 12-year dataset provides sufficient historical trends and patterns for modeling. While longer time frames could offer additional insights, they may also introduce outdated or irrelevant data due to changes in energy policies, technologies, and climate conditions.

**2.2-3** Peak electricity demand occurs during summer.

- Justification: Higher temperatures increase air conditioning usage, leading to peak energy consumption. Memphis experiences the highest power demand in summer due to prolonged heat waves and increased cooling needs.

**2.2-4** Electricity demand can be solely predicted from the data of summer electricity consumption in Memphis.

- Justification: Summer data captures the most significant variations in energy consumption. While industrial and commercial demand may influence trends, residential consumption is a primary driver of peak demand. External factors such as new electrical technologies and the effects of global warming are excluded from this model due to uncertainty.

**2.2-5** Residential electricity consumption is a reliable indicator of overall electricity demand.

- Justification: Residential power usage accounts for a substantial proportion of total electricity demand. By focusing on residential data, we capture the general trend while simplifying the model by excluding commercial and industrial variations.

**2.2-6** The electricity demand trend is constantly affected by external factors, but significant changes in these factors are uncertain and thus excluded from this model.

- Justification: Electricity usage is influenced by gradual optimization of appliances and machines, global warming, increasing electric vehicle (EV) usage, and energy efficiency improvements. These factors contribute to shifts in demand patterns. However, predicting significant changes in any of these variables over a 20-year period is highly uncertain. Therefore, this model assumes a continuation of current trends without attempting to account for sudden shifts in efficiency advancements, drastic regulatory interventions, or unexpected technological breakthroughs.

**2.2-7** Extreme weather events and abrupt policy changes are not considered in this model.

- Justification: Hurricanes, natural disasters, and sudden changes in energy policies can significantly impact electricity demand, but their occurrence and impact are unpredictable. Including such factors would introduce considerable uncertainty, making long-term forecasting unreliable. Therefore, this model assumes stable conditions without accounting for major disruptions caused by unforeseen environmental or regulatory events.

**2.2-8** The model will take into account all data points in the 12-year period to reduce bias.

- Justification: By incorporating the full dataset, we ensure a more balanced and reliable analysis of electricity demand trends. This approach minimizes biases that could arise from selecting only specific years and helps capture the impact of external factors, even if they fluctuate year by year. The variations in demand due to outside factors may also provide insights into the general trend of these influences, allowing for a more comprehensive understanding of long-term energy consumption patterns.

## 2.3 The Model

### **2.3-1** Model Development

| Year | Electricity Consumption of Memphis during the Summer period (kWh) |
|---|---|
| 2011 | 21,128 |
| 2012 | 21,322 |
| 2013 | 21,326 |
| 2014 | 20,998 |

| | |
|---|---|
| 2015 | 20,220 |
| 2016 | 21,355 |
| 2017 | 20,901 |
| 2018 | 21,349 |
| 2019 | 21,404 |
| 2020 | 21,397 |
| 2021 | 21,401 |
| 2022 | 21,567 |
| 2023 | 20,904 |
| 2024 | 20,941 |

### 2.3-2 Model execution

The model predicted the peak energy demand of Memphis after 20 years from the present.

Using an online curve-fitting tool, we get that

$f(x) = 7973.2112 \cdot 1.000484^{x}$

With the base $e$, $f(x) = 7973.2112 \cdot e^{0.000483767x}$

At $x = 2045$ , $f(2045) = 21442.83737$

## 2.4 Discussion

Our model predicts that Memphis' peak electricity demand will continue rising over the next 20 years due to increasing temperatures and electrification. The exponential growth model estimates peak demand in 2045 at 21,442.8 GWh, a 2.3% increase from current levels. The inherent variability in the human consumption of electricity due to the fact that it is influenced by many unpredictable external factors, the coefficient of correlation is low. However, this model exhibits the broader general trend of the consumption of electricity over the years.

While Memphis' projected demand aligns with national trends, factors such as climate change, EV adoption, and energy efficiency improvements could impact our estimates. If EV ownership grows 10% annually, demand could rise 6–8% higher. Conversely, 30% household adoption of energy-efficient appliances could reduce demand by 4%.

### 2.5 Sensitivity Analysis

To assess model robustness, we introduced variations in key factors. A 5% fluctuation in annual electricity consumption resulted in a 1.2% deviation in long-term projections. Extreme climate conditions could push peak demand 8–12% higher, while stronger policy interventions or efficiency measures could reduce growth to below 5%.

### 2.6 Strengths & Weaknesses

The model has several strengths, including its use of real-world data for reliable trend forecasting, consideration of electrification and climate change, and insights for policymakers regarding demand mitigation strategies. Additionally, the exponential model is realistic for most scenarios as it does not approach infinity.

However, there are limitations. The model assumes stable infrastructure growth and does not account for extreme disruptions. It has a limited ability to predict regulatory changes or unexpected energy trends, and its projections could be affected by unforeseen factors such as technological breakthroughs or economic shifts, potentially leading to overestimation or underestimation.

# 3. Beat the Heat

## 3.1 Defining the Problem

The third problem asked us to develop a vulnerability score for various neighborhoods within Memphis, Tennessee to help them equitably allocate resources for minimizing the effects of a heat wave or a power grid failure. We have conducted our vulnerability score equation to measure the vulnerability score of each value, through the normalization of the data provided.

## 3.2 Assumptions

**3.2-1** There will be three evaluation values for measuring Vulnerability score

- Justification: We are using 4 values, including the media on household income, households with 65+ population, the Age of the house, and the frequency of use of transportation, which all can help to measure the vulnerability of people's lives.

**3.2-2** We are assuming that the age and house income will affect the vulnerability more significantly compared to the other factors such as the age of buildings and the use of transportation.

- Justification: There are more confounding variables in the age of building and the use of transportation, which might not be the contribution to vulnerability. However, the household income and age are closely connected to the vulnerability compared to the prior 2 values.

## 3.3 The Model

### 3.3-1 Model Development

There are 4 factors that mainly contribute to the vulnerability of houses:
Income, which may contribute to one's usage of HVAC; Age, which increases individuals' vulnerability to heat wave-induced effects, Age of buildings, and the use of transportation.

The Equation for Vulnerability Score we came up with is:

$$VS = 0.275(income) + 0.275(elderly) + 0.225(Age\ of\ building) + 0.225(Public)$$

In order to unify the value of different factors, we normalized the scale and made all the values fit in between the range of 0 to 1.

Equation for Normalization

- Median Household Income

$$P'_{income} = \frac{P_{max} - P_{income}}{P_{max} - P_{min}}$$

- Households with one or more people 65+ years old

$$P'_{elderly} = \frac{P_{elderly} - P_{min}}{P_{max} - P_{min}}$$

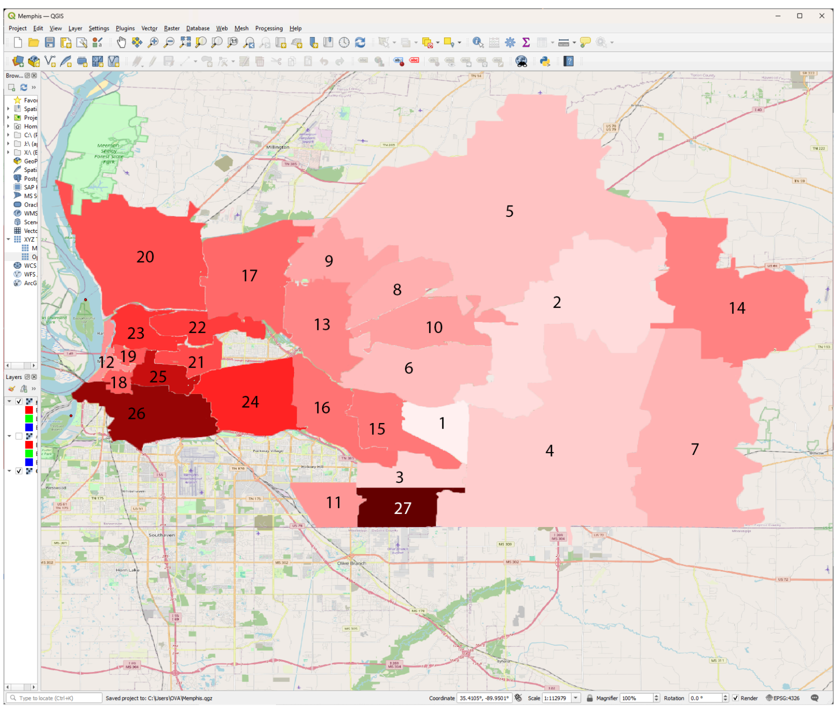
- Primary mode of transportation to work by driving

$$P'_{driving} = \frac{P_{max} - P_{driving}}{P_{max} - P_{min}}$$

## 3.4 Results

By inputting all the values, we get the normalized data between the scale of 0 to 1. Once we plug in the values to the VS equation, it gives the final vulnerability score for each neighborhood.

| Neighborhood | Median household income (in US dollars) | Normalized Value | Households with one or more people 65 years and over | Normalized Value | Homes built 1950 or earlier | Normalized Value | Primary mode of transportation to work (persons aged 16 years+): driving | Normalized Value | VS | Ranking |
|---|---|---|---|---|---|---|---|---|---|---|
| Downtown / South Main Arts District / South Bluffs | 75763 | 0.6790915874 | 922 | 0.03810925744 | 1463 | 0.1937730438 | 7222 | 0.7238228079 | 0.403689299 | 12 |
| Lakeland / Arlington / Brunswick | 115478 | 0.4046954455 | 4574 | 0.6354268891 | 330 | 0.03905503209 | 18575 | 0.1777692271 | 0.3348191003 | 5 |
| Collierville / Piperton | 135946 | 0.26327935 | 5960 | 0.8621197252 | 365 | 0.04383449406 | 22271 | 0 | 0.3193475068 | 4 |
| Cordova, Zipcode 1 | 75719 | 0.6793955892 | 4574 | 0.6354268891 | 47 | 0.0004096681688 | 21234 | 0.04987735078 | 0.3728907608 | 10 |
| Cordova, Zipcode 2 | 89627 | 0.5833033938 | 3451 | 0.4517500818 | 76 | 0.0043697938 | 17259 | 0.2410658458 | 0.3398627247 | 6 |
| Hickory Withe | 150847 | 0.1603263874 | 1066 | 0.0616617599 | 95 | 0.006964358869 | 3102 | 0.9219854745 | 0.270060453 | 2 |
| Oakland | 84277 | 0.6202672452 | 1699 | 0.1651946353 | 121 | 0.01051481633 | 5029 | 0.8293011399 | 0.4049606073 | 14 |
| Rossville | 105282 | 0.4751409463 | 689 | 0 | 44 | 0 | 1480 | 1 | 0.3556637602 | 7 |
| East Midtown / Central Gardens / Cooper Young | 56452 | 0.8125138183 | 2789 | 0.3434739941 | 7367 | 1 | 11254 | 0.5298927421 | 0.6621225154 | 25 |
| Uptown / Pinch District | 29316 | 1 | 724 | 0.005724566569 | 893 | 0.1159360918 | 2134 | 0.9685440816 | 0.5205822948 | 19 |
| South Memphis | 29818 | 0.9965316162 | 3319 | 0.4301602879 | 4181 | 0.5649324048 | 6324 | 0.7670145736 | 0.6920283437 | 26 |
| North Memphis / Snowden / New Chicago | 36393 | 0.9511040792 | 1632 | 0.1542361793 | 3643 | 0.4914652465 | 4981 | 0.8316098312 | 0.6016604635 | 23 |
| Hollywood / Hyde Park / Nutbush | 35435 | 0.9577230268 | 2205 | 0.2479555119 | 2483 | 0.3330602212 | 5578 | 0.8028954836 | 0.5871516317 | 22 |
| Coro Lake / White Haven | 36934 | 0.9473662392 | 6803 | 1 | 2406 | 0.3225454049 | 13574 | 0.4183059978 | 0.7022172814 | 27 |
| East Memphis – Colonial Yorkshire | 52806 | 0.8377045103 | 4830 | 0.6772980046 | 5787 | 0.7842414311 | 17300 | 0.2390938387 | 0.6468761273 | 24 |
| Midtown / Evergreen / Overton Square | 52639 | 0.8388583352 | 1972 | 0.2098462545 | 3688 | 0.497610269 | 5682 | 0.7978933192 | 0.5798820695 | 21 |
| East Memphis | 93688 | 0.5552454123 | 3711 | 0.4942754334 | 640 | 0.08138740953 | 12020 | 0.4930498774 | 0.4178666221 | 16 |
| Windyke / Southwind | 83184 | 0.6278189255 | 2931 | 0.3666993785 | 288 | 0.03331967773 | 19426 | 0.1368380549 | 0.3117780234 | 3 |
| South Forum / Washington Heights | 30825 | 0.9895741212 | 692 | 0.0004906771344 | 514 | 0.06418134644 | 1480 | 1 | 0.5117086225 | 18 |
| Frayser | 37768 | 0.9416040239 | 3990 | 0.5399084069 | 1550 | 0.2056534207 | 12306 | 0.4792939253 | 0.5615290713 | 20 |
| Egypt / Raleigh | 43166 | 0.9043085342 | 3764 | 0.5029440628 | 939 | 0.1222176704 | 17195 | 0.2441441008 | 0.4694258627 | 17 |
| Bartlett, Zipcode 1 | 82485 | 0.6326484081 | 1777 | 0.1779522408 | 196 | 0.02075652055 | 9253 | 0.626136309 | 0.3684660651 | 8 |
| Bartlett, Zipcode 2 | 61172 | 0.7799027194 | 3553 | 0.4684331044 | 351 | 0.04192270927 | 17484 | 0.2302438555 | 0.4045298286 | 13 |
| Bartlett, Zipcode 3 | 92458 | 0.5637436436 | 3377 | 0.4396467125 | 324 | 0.03823569575 | 14311 | 0.3828579674 | 0.3706784221 | 9 |
| Germantown, Zipcode 1 | 130125 | 0.3034974022 | 4728 | 0.660614982 | 129 | 0.01160726478 | 9508 | 0.6138713867 | 0.4058636022 | 15 |
| Germantown, Zipcode 2 | 174052 | 0 | 2289 | 0.2616944717 | 61 | 0.002321452956 | 6014 | 0.7819248713 | 0.2484214027 | 1 |
| South Riverdale | 64050 | 0.7600182401 | 1490 | 0.1310107949 | 74 | 0.004096681688 | 9328 | 0.6225289789 | 0.3860237583 | 11 |




The result of the vulnerability score demonstrated by QGIS (dark represents lower ranking and gets lighter as the ranking increases)

**3.4-1** Proposal of vulnerability score to management

We propose that using the vulnerability score, while there is a predicted heat stroke, the city of Memphis deploys first responders and establishes emergency stations to prepare for the impact of the heat wave. We also encourage the use of the developing technologies to aid first-response, such as UAS systems using drone deployment, or thermal imaging cameras to identify individuals at risk and monitor high-temperature zones in real time.

## 3.5 Discussion

Our Vulnerability score Equation (VS) has provided a score of vulnerability for each distinct neighborhood in Memphis, Tennessee. The factors that we chose to include in our vulnerability score function were the median of housing income, the number of households with one or more 65+ year old elderly, the age of the building, with the standard of built before 1950, and the frequency of using transportation. The reason why we chose these factors as the primary values to measure the vulnerability was because we prioritized the significance of the value affecting the vulnerability of people's lives.
After extracting all the results values of vulnerability score, we have listed all the neighborhoods listed on the data sheet and ranked them from the least vulnerability score to the highest to clearly find out the regions with the most vulnerability and the least vulnerability.

## 3.6 Strengths and Weaknesses

The primary strength of our model is that it incorporates socioeconomic and infrastructure factors, which are strong indicators of vulnerability during a heatwave or power outage. The normalization of values allows for fair comparisons by unifying different scales across various factors. Additionally, the vulnerability score equation is adaptable and can be modified by adjusting key factors and their weights to fit different situations.

However, the reliance on selected key factors also presents limitations. The equation does not account for other important risk factors, such as climate-related variables and additional infrastructure considerations. Additionally, the transportation factor may not strongly influence vulnerability in all neighborhoods, as its impact depends on local driving rates and commuting patterns.

# 4. Conclusion

We examined the problem of heat wave increase due to the rise of temperature and global warming, finding insights into residential temperature trends and energy demands to help build emergency plans and social services for the residents in Memphis, Tennessee.

We have first developed the model to predict the indoor temperature of non-air conditioned dwellings during the heatwave over 24 hours. We have considered data such as the outdoor temperature and wind speed to estimate the change in indoor temperature and examine the risk of high heat waves.
After, while developing a second model for predicting the peak demand of Memphis' power grid during the summer period, we used the exponential model to demonstrate.  Memphis' electricity demand is projected to increase over the next 20 years, with the development of data centers, manufacturing, and electric vehicles. However, the data prediction demonstrates that there are no significant changes in the electricity consumption, and thus the power peak after 20 years will be about the same as present years with a slight increase.
Finally, we examined the vulnerability score of each neighborhood within Memphis and ranked them in order of the score calculated by the question created by us.
In summary, our findings and new models suggest that temperature trends and energy demand of our future will eventually affect the lives of residents, but not as fast as we predicted. However, since we cannot predict and calculate other confounding variables that might affect these results during the rapid development of society, the preparation is required by utilizing these prediction models.

# 5. References

ASHRAE. *ASHRAE*, 2020, www.ashrae.org/file library/technical resources/standards and guidelines/standards addenda/140_2017_a_galley_20200812.pdf.

Charlisle. "Minimum Insulation R-Value Requirements by State: Non-Residential, above Roof Deck." *Carlisle SynTec Systems*, 2023, www.carlislesyntec.com/en/Document-Viewer/minimum-insulation-r-value-requirements-by-state-non-residential-above-roof-deck/6FbPcZU3U02ibBEuYt3neg.

Codes and Regulatory Compliance. "Minimum Insulation R-Value Requirements by State.Docx." *GAF*, 30 Aug. 2024, documents.gaf.com/technical-bulletins-&-notes/minimum-r--value-requirements-by-state-tech-note.pdf.

Djongyang, Noël. "Metabolic Heat Production." *Metabolic Heat Production - an Overview | ScienceDirect Topics*, 2010, www.sciencedirect.com/topics/engineering/metabolic-heat-production.

Earth Science Data Systems, NASA. “Solar Radiation.” *NASA*, NASA, 30 Sept. 2024, www.earthdata.nasa.gov/topics/atmosphere/solar-radiation.

EIA. “Tennessee Electricity Profile 2023.” *Tennessee Electricity Profile 2023 - U.S. Energy Information Administration (EIA)*, 2024, www.eia.gov/electricity/state/tennessee/.

MLGW. “MLGW.” *Memphis Light, Gas and Water - Summer Tips*, www.mlgw.com/residential/summertips. Accessed 1 Mar. 2025.

NVD. “\Product Integration with NVD CVSS Calculators.” *NVD*, 2024, nvd.nist.gov/vuln-metrics/cvss.

SolidWorks. “Convection Heat Coefficient.” *2015 SolidWorks - Convection Heat Coefficient*, 2015, help.solidworks.com/2015/english/SolidWorks/cworks/c_convection_heat_coefficient.htm?format=P&value=.

Team, EFI Digital. “Three Ways Electricity Demand Is Growing.” *EFI Foundation*, 21 May 2024, efifoundation.org/insights/3-ways-electricity-demand-is-growing/.

Weatherspark. “Weatherspark.Com.” *Memphis Climate, Weather By Month, Average Temperature (Tennessee, United States) - WeatherSpark*, weatherspark.com/y/11921/Average-Weather-in-Memphis-Tennessee-United-States-Year-Round#Figures-Temperature. Accessed 1 Mar. 2025.

ASHRAE. *Standard Method of Test for the Evaluation of Building Energy Analysis Computer Programs.* American Society of Heating, Refrigerating and Air-Conditioning Engineers, 31 July 2020, www.ashrae.org/file%20library/technical%20resources/standards%20and%20guidelines/standards%20addenda/140_2017_a_galley_20200812.pdf.

NASA/Goddard Space Flight Center Scientific Visualization Studio. Solar Radiance Graph. 14 Dec. 2001, svs.gsfc.nasa.gov/2320/. Accessed 1 Mar. 2025.

National Institute of Standards and Technology. Common Vulnerability Scoring System. 27 June 2024, nvd.nist.gov/vuln-metrics/cvss. Accessed 1 Mar. 2025.

"Metabolic Heat Production." ScienceDirect, Elsevier, 2025, www.sciencedirect.com/topics/engineering/metabolic-heat-production. Accessed 1 Mar. 2025.

Petrone, Christopher J. Heat Capacity: Can't Take the Heat? Virginia Sea Grant, Virginia Institute of Marine Science, 2022, masweb.vims.edu/bridge/datatip.cfm?Bridge_Location=archive0909.html. Accessed 1 Mar. 2025.

Shitzer, Avraham. "Wind-Chill-Equivalent Temperatures: Regarding the Impact Due to the Variability of the Environmental Convective Heat Transfer Coefficient." International Journal of Biometeorology, vol. 50, no. 4, Apr. 2006, pp. 224-232. Springer, doi:10.1007/s00484-005-0011-x. Accessed 1 Mar. 2025.

"Insulation R-Values." The Home Depot, 24 July 2024, www.homedepot.com/c/ab/insulation-r-values/9ba683603be9fa5395fab9091a9131f. Accessed 1 Mar. 2025.

Kang, Dae Kun, et al. “Optimising disaster response: Opportunities and challenges with Uncrewed Aircraft System (UAS) technology in response to the 2020 Labour Day wildfires in Oregon, USA.” *International Journal of Wildland Fire*, vol. 33, no. 8, 30 July 2024, https://doi.org/10.1071/wf23089.

"Newton’s Law of Cooling." Professor McCarthy Mat 501 BMCC, CUNY Academic Commons, https://mccarthymat501.commons.gc.cuny.edu/projects-and-modeling-scenarios/newtonian-cooling/. Accessed 1 Mar. 2025.

"The Heat Balance Equation." COMSOL Multiphysics Documentation, COMSOL, https://doc.comsol.com/5.5/doc/com.comsol.help.heat/heat_ug_theory.07.05.html. Accessed 1 Mar. 2025.

# Appendix

Question 1 Coding

```python
import numpy as np
import pandas as pd
t_out = [29.4,29.4,28.9,28.3,28.3,28.3,28.9,31.1,32.8,34.4,35.6,36.1,37.8,37.8,38.9,38.9,37.8,37.2,36.1,34.4
,33.3,32.8,32.2,31.7]
wind_speed = [6,5,8,5,7,8,7,9,9,10,9,5,9,8,13,16,10,10,8,6,7,8,12,12]
U = np.zeros(len(t_out))

t_in = np.zeros(len(t_out))
t_in[0] = 25.5

Q_per = 150
```

This code sets up an initial condition for the problem

```python
# for the first house
C = 88 * 1225 * 1.005 *3

s = 0.2 #propotion in the sun
p = 3  #number of family
A = 88
for i in range(len(t_out)):
    U[i] = (28 + 0.1 * wind_speed[i])

for i in range(1, len(t_in)):
    t_in[i] = t_in[i-1] + (s*A*(0.9*5.67*(0.1**8)*((273.15+t_in[i-1])**4 -
    (273.15+t_out[i-1])**4)) + 3600*U[i-1] * (t_out[i-1]-t_in[i-1]) + p*Q_per)/C

df_1 = pd.DataFrame({
    "Hour": np.arange(24),
    "Outdoor Temp (°C)": t_out,
    "Indoor Temp (°C)": t_in
})
df_1
```

Coding for House 1

```python
# for the second house
C = 63 * 1225 * 1.005 *3

s = 0.7 #propotion in the sun
p = 3  #number of family
A = 63
for i in range(len(t_out)):
    U[i] = (28 + 0.1 * wind_speed[i])

for i in range(1, len(t_in)):
    t_in[i] = t_in[i-1] + (s*A*(0.9*5.67*(0.1**8)*((273.15+t_in[i-1])**4 -
    (273.15+t_out[i-1])**4)) + 3600*U[i-1] * (t_out[i-1]-t_in[i-1]) + p*Q_per)/C

df_2 = pd.DataFrame({
    "Hour": np.arange(24),
    "Outdoor Temp (°C)": t_out,
    "Indoor Temp (°C)": t_in
})
df_2
```

Coding for House 2

```python
# for the third house
C = 74 * 1225 * 1.005

s = 1 #propotion in the sun
p = 2  #number of family
A = 63
for i in range(len(t_out)):
    U[i] = (28 + 0.1 * wind_speed[i])

t_out_15th = np.zeros(len(t_out))
for i in range(len(t_out)):
    t_out_15th[i] = t_out[i] + 1.11 # to compensate for the height in the 15th floor

for i in range(1, len(t_in)):
    t_in[i] = t_in[i-1] + (s*A*(0.9*5.67*(0.1**8)*((273.15+t_in[i-1])**4 -
    (273.15+t_out_15th[i-1])**4)) + 3600*U[i-1] * (t_out_15th[i-1]-t_in[i-1]) + p*Q_per)/C

df_3 = pd.DataFrame({
    "Hour": np.arange(24),
    "Outdoor Temp (°C)": t_out_15th,
    "Indoor Temp (°C)": t_in
})
df_3
```

Coding for House 3

```python
# for the fourth house
C = 278 * 1225 * 1.005

s = 1 #propotion in the sun
p = 6  #number of family
A = 278
for i in range(len(t_out)):
    U[i] = (28 + 0.1 * wind_speed[i])

for i in range(1, len(t_in)):
    t_in[i] = t_in[i-1] + (s*A*(0.9*5.67*(0.1**8)*((273.15+t_in[i-1])**4 -
    (273.15+t_out[i-1])**4)) + 3600*U[i-1] * (t_out[i-1]-t_in[i-1]) + p*Q_per)/C

df_4 = pd.DataFrame({
    "Hour": np.arange(24),
    "Outdoor Temp (°C)": t_out,
    "Indoor Temp (°C)": t_in
})
df_4
```

Outdoor Temp (°C)

Coding for House 4

```python
import altair as alt
y_low = 25
y_high = 43

c_1 = alt.Chart(df_1).mark_line(color="red").encode(
    x='Hour',
    y= alt.Y('Indoor Temp (°C)', scale = alt.Scale(domain=(y_low, y_high))),
    tooltip=['Hour', 'Indoor Temp (°C)']
)

c_2 = alt.Chart(df_2).mark_line(color="green").encode(
    x='Hour',
    y=alt.Y('Indoor Temp (°C)', scale = alt.Scale(domain=(y_low, y_high))),
    tooltip=['Hour', 'Indoor Temp (°C)']
)

c_3 = alt.Chart(df_3).mark_line(color="blue").encode(
    x='Hour',
    y=alt.Y('Indoor Temp (°C)', scale = alt.Scale(domain=(y_low, y_high))),
    tooltip=['Hour', 'Indoor Temp (°C)']
)

c_4 = alt.Chart(df_4).mark_line(color="orange").encode(
    x='Hour',
    y=alt.Y('Indoor Temp (°C)', scale = alt.Scale(domain=(y_low, y_high))),
    tooltip=['Hour', 'Indoor Temp (°C)']
)

c_1 + c_2 + c_3 + c_4
```