



Weather Dependent Forced Outage Model

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- At the January RASTF meeting (<https://www.pjm.com/-/media/committees-groups/task-forces/rastf/2023/20230118/item-02a---rastf-high-level-design-concepts---pjm.ashx>), PJM presented the basic concepts around a Weather Dependent Forced Outage Model. Specifically,
 - How the EFORd concept is connected with Markov Chain transition matrices

Markov Chain Transition Matrix

	A	F
A	0.961	0.039
F	0.125	0.875



Steady State

	Prob
A	0.76
F	0.24

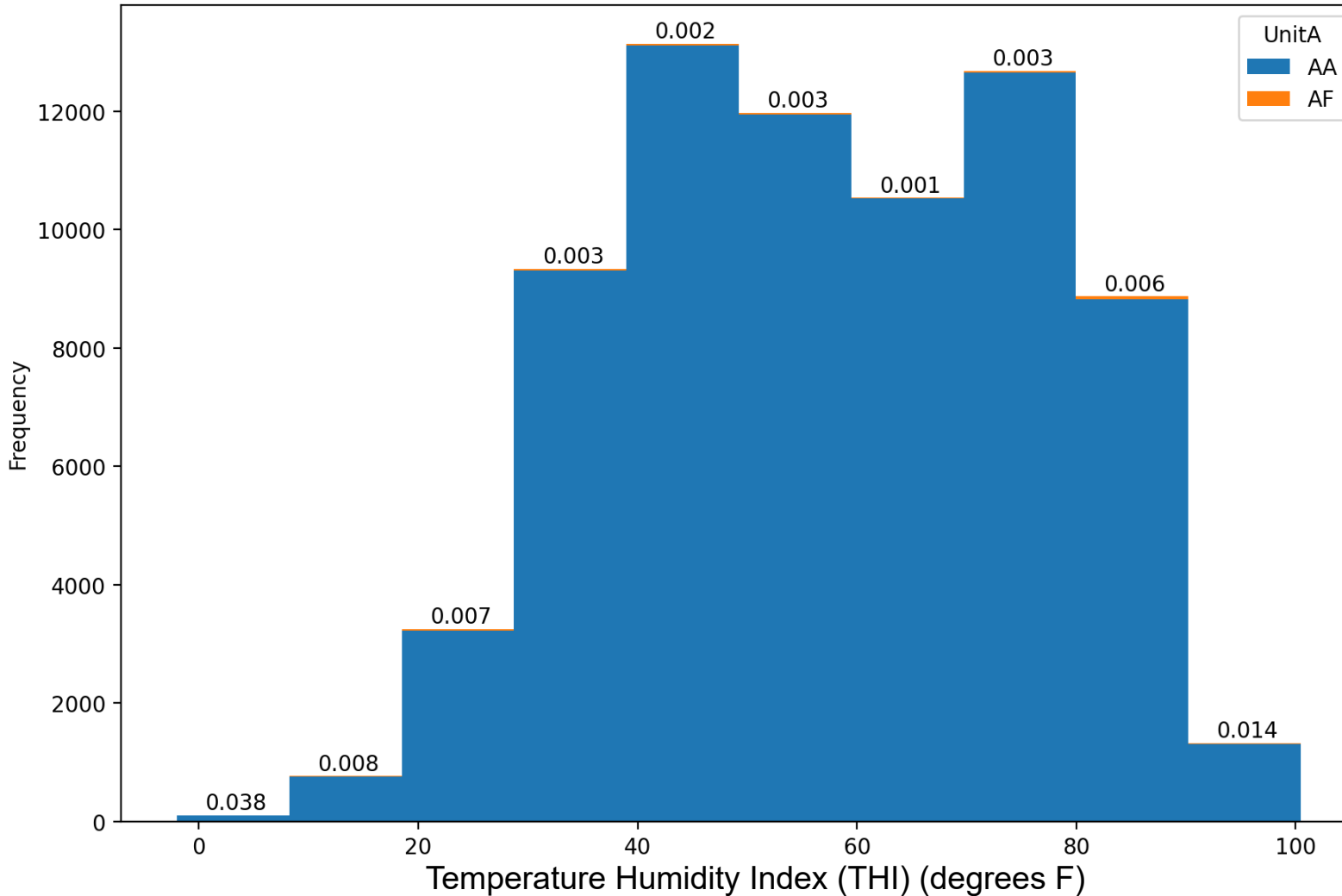
EFORd of the unit

- How the transition probabilities in the above transition matrix can be calculated as a function of temperature using historical data and a logistic regression model

- Today, we will focus on an actual specific unit (Unit A) to illustrate the concepts. Specifically,
 - How the historical outage data of Unit A is used by the logistic regression model to derive transition probabilities as a function of temperature
 - And how the transition probabilities are used in a Monte Carlo framework to derive multiple outage scenarios of Unit A for given temperature values

Histogram: Temperature vs AA and AF transition for Unit A

UnitA - Histogram AA, AF

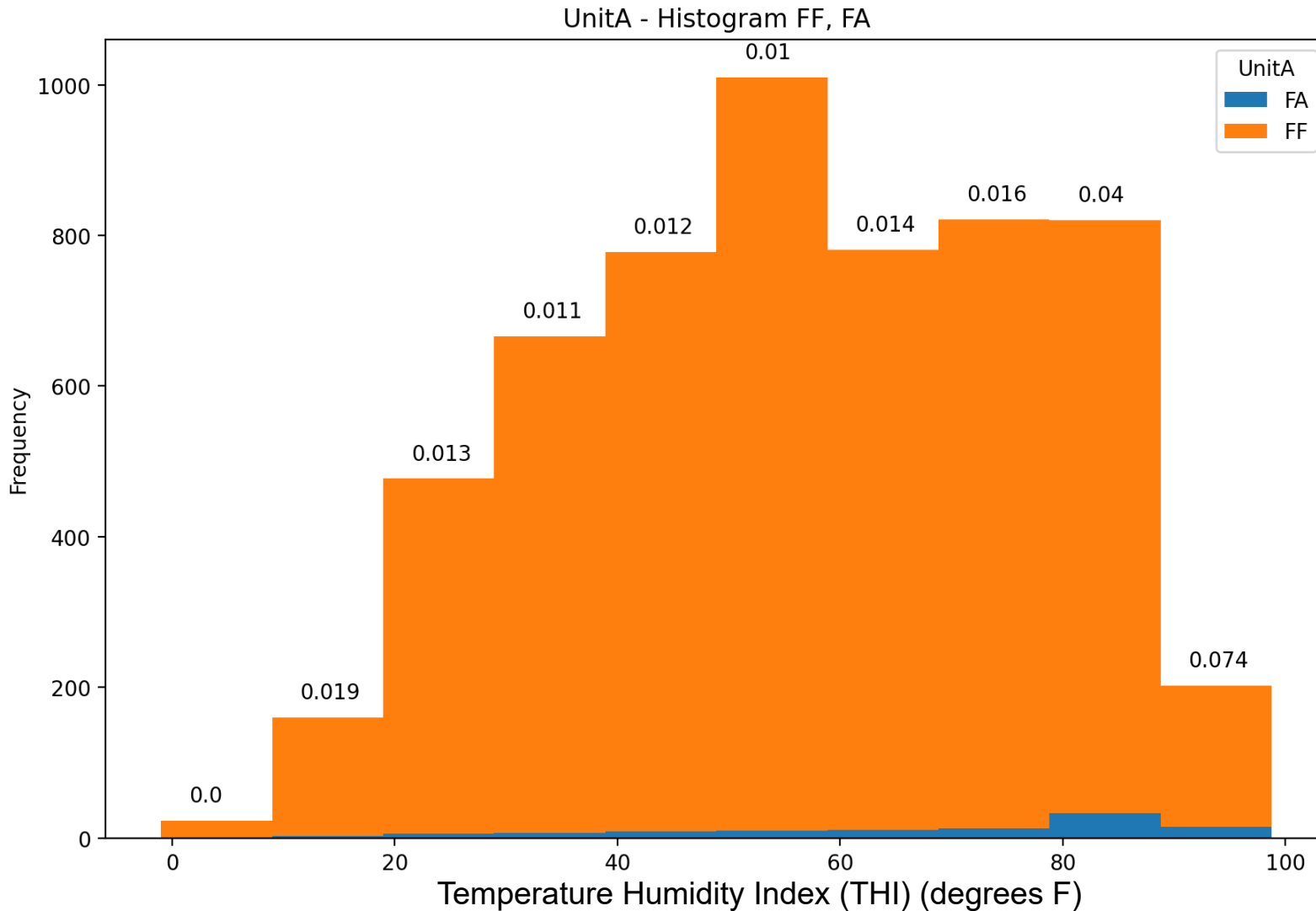


The height of the bars tells us how often the unit experienced the temperature in the x-axis when the unit was Available. While this is important, it is not the key element in the graph

The key element in the graph is the share of orange in each of the bars (shown as the value on top of each bar)

The larger the share, the more often the unit moved to a Forced Outage state from an Available state when experiencing the temperatures in the x-axis

Histogram: Temperature vs FF and FA transition for Unit A

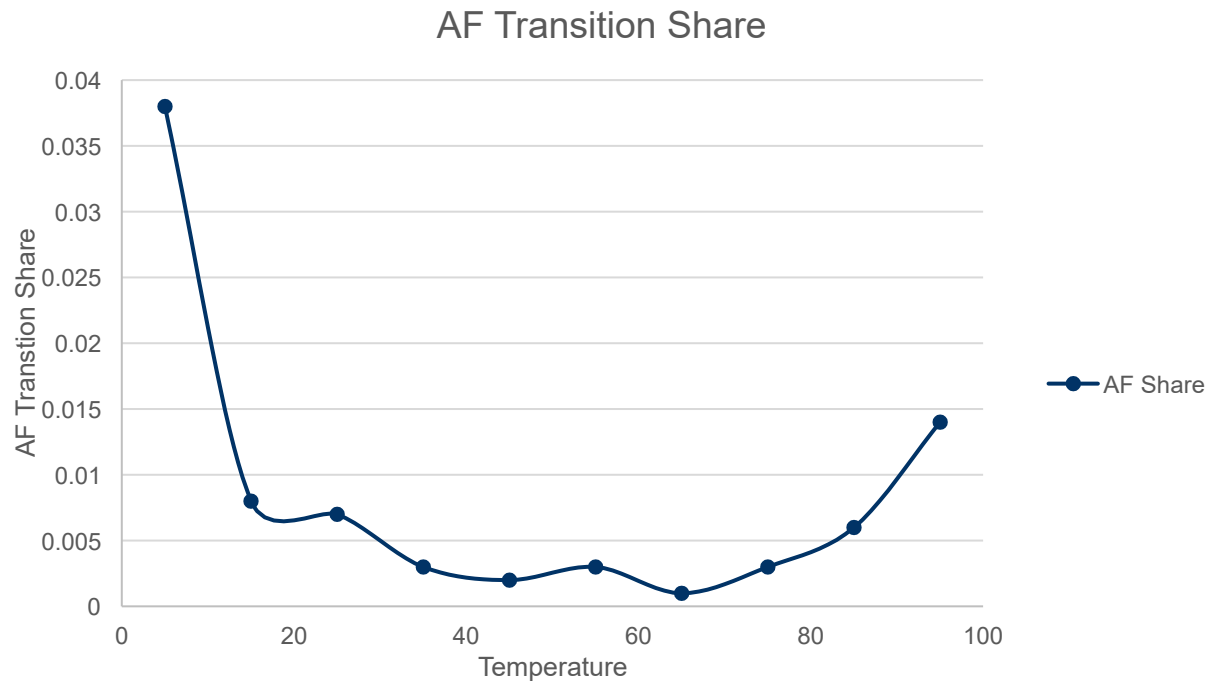


The height of the bars tells us how often the unit experienced the temperature in the x-axis when the unit was Forced Out. While this is important, it is not the key element in the graph

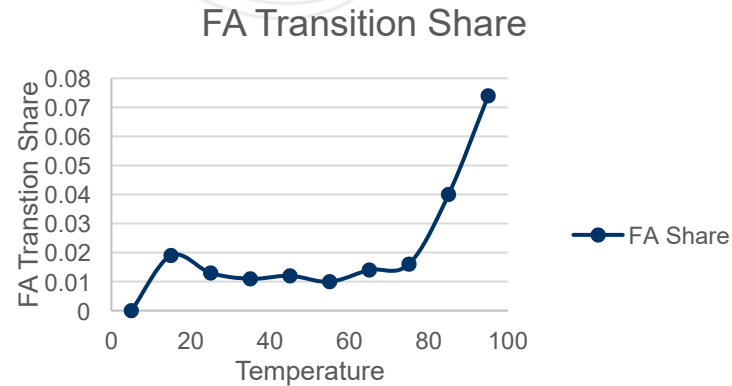
The key element in the graph is the share of blue in each of the bars (shown as the value on top of each bar)

The larger the share, the more often the unit moved to the Available state from Forced Out when experiencing the temperatures in the x-axis

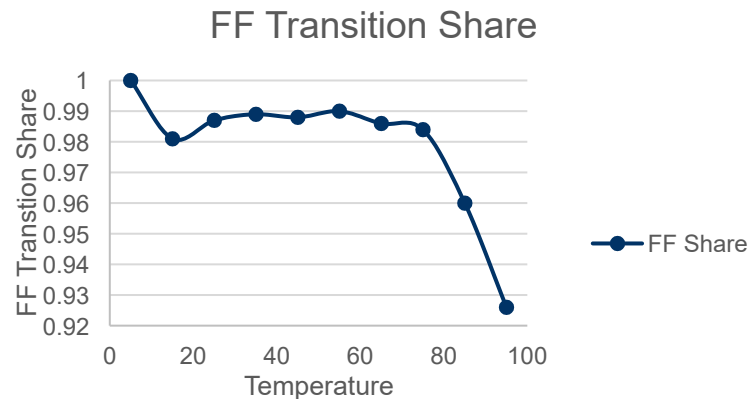
- From the first histogram, if we plot the AF Transition Share vs Temperature, we get the following



- From the second histogram, if we plot the FA Transition Share vs Temperature we get the following



- We can also derive the FF Transition Share vs Temperature

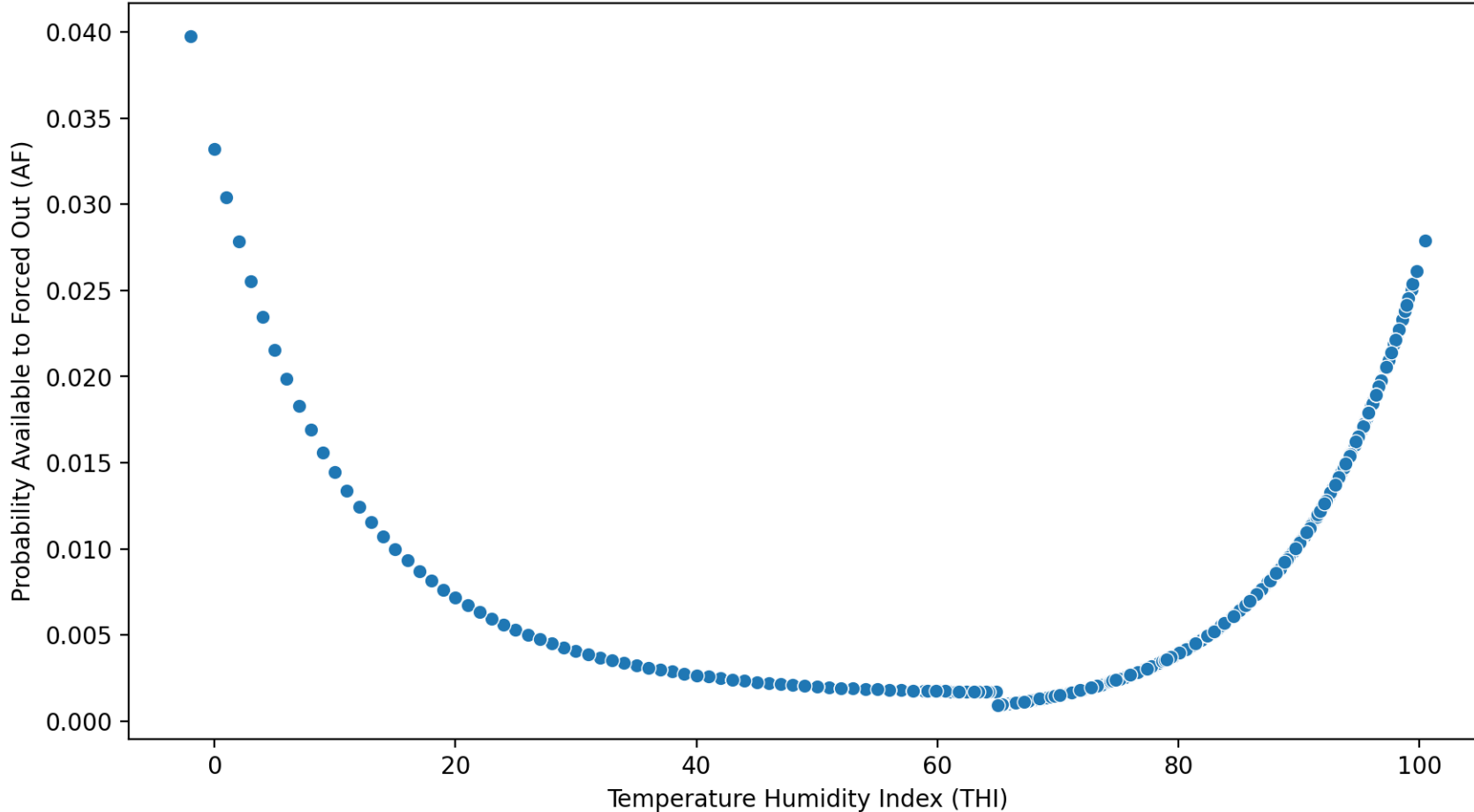


- Conclusions about the Forced Outage pattern based on temperature for Unit A should be made by looking at **both** histograms
 - If we look at the two extremes of the first histogram, we can see that Unit A transitions to Forced Out from Available more often when it gets really cold and when it gets really hot
 - However, if we look at the two extremes of the second histogram, we can see that Unit A transitions to Available from Forced Out more often only when it gets really hot, while when it gets really cold it lingers on the Forced Out state
 - From the two points above, we can conclude that Unit A spends more time Forced Out when it gets really cold than when it gets really hot



Probability of Transition from Available to Forced Out in an Hour as a function of temperature for Unit A using logistic regression

UnitA - Probability of Transition from Available to Forced Outage in an Hour



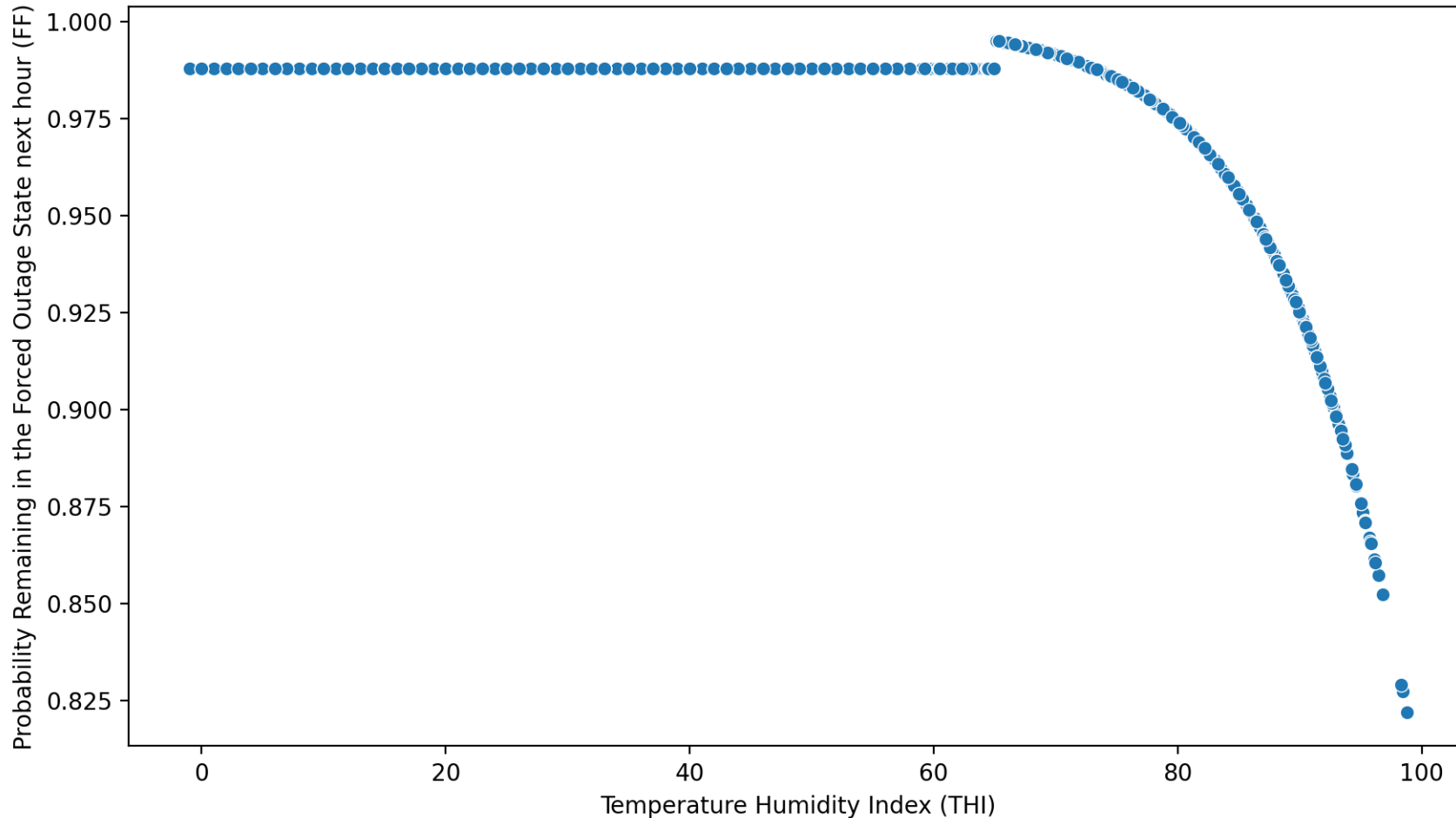
Specification of logistic regression model that better matches the historical data when Unit A is in the Available State in an hour and either remains Available in the next hour or transitions to the Forced Out state in the next hour

$$\text{UnitA} \sim \frac{\text{constant_hot} + \text{constant_cool} + \text{degrees_hot} + \text{degrees_cool}^2}{1 + \exp(\dots)}$$



Probability of Remaining in a Forced Outage in next hour as a function of temperature for Unit A using logistic regression

UnitA - Probability of Remaining in a Forced Outage in next Hour



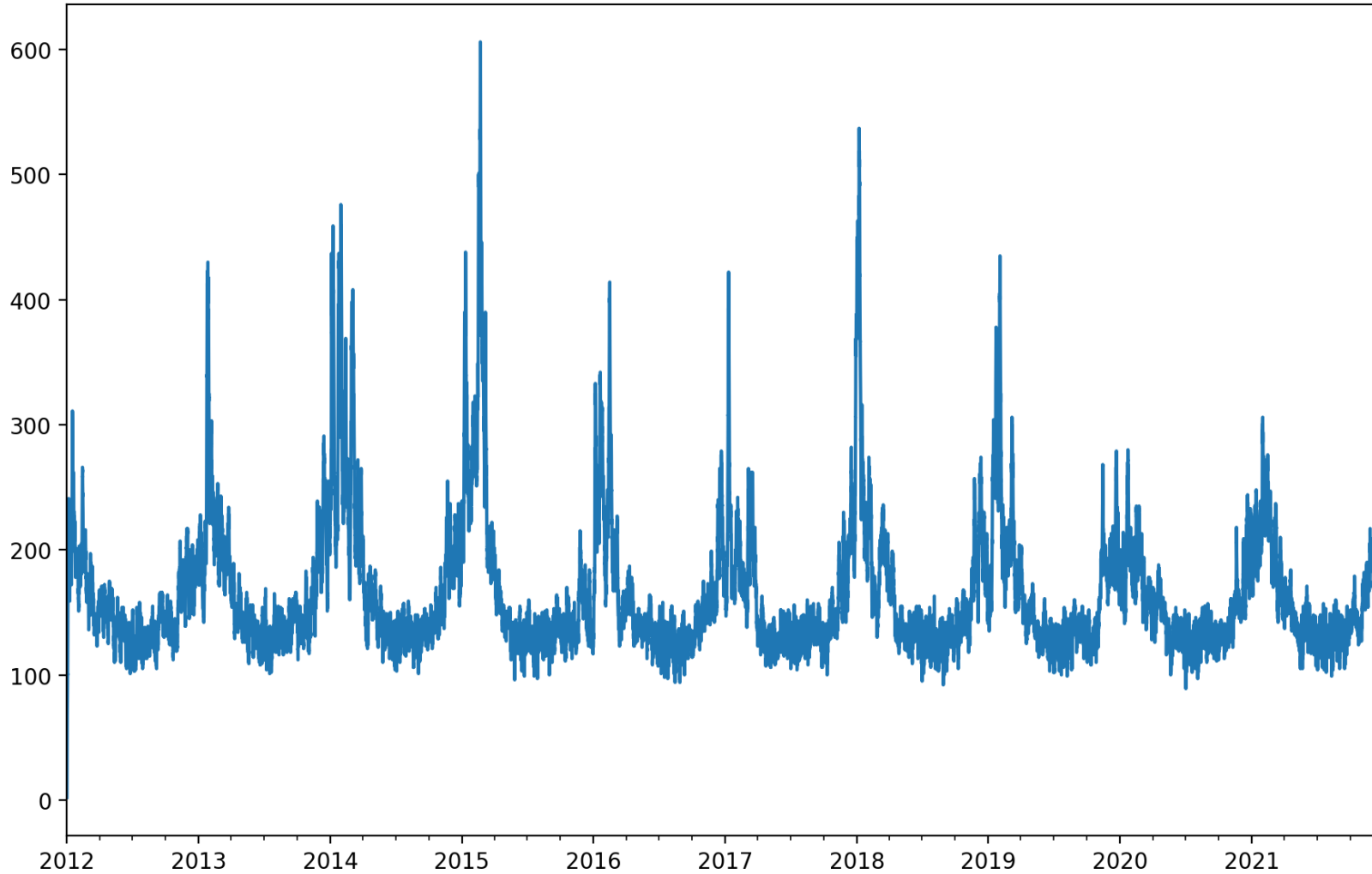
Specification of logistic regression model that better matches the historical data when Unit A is in the Forced Out State in an hour and either remains Forced Out in the next hour or transitions to the Available state in the next hour

$$\text{UnitA} \sim \text{constant_hot} + \text{constant_cool} + \text{degrees_hot} - 1$$



Using the weather dependent transition probabilities in a Monte Carlo framework to derive multiple outage scenarios for given temperature values

UnitA - 1000 Reps Result



The graph shows the number of replications (out of 1000) in which Unit A is modeled as Forced Out as a function of the temperature experienced by the unit in the hour shown in the x-axis

- On 02/20/15 at 8 AM, in 532 of the 1000 scenarios Unit A is modeled on a Forced Outage
- On 01/07/14 at 7 PM, in 393 of the 1000 scenarios Unit A is modeled on a Forced Outage
- On 07/17/12 at 5 PM, in 115 of the 1000 scenarios Unit A is modeled on a Forced Outage
- On 07/18/13 at 5 PM, in 112 of the 1000 scenarios Unit A is modeled on a Forced Outage