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# Observing parking at UCF with AI

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**ABSTRACT**
Team number: 216
Track: 2
The code is available at https://github.com/MichaelHopwood/UCFParkingAI.

**INDEX TERMS** parking, monitoring system, generalized low rank models

## I. INTRODUCTION

The University of Central Florida has an enrollment size of 70,000 students and parking is very limited throughout the campus. This parking issue has led to students and faculty arriving late for classes, loss class time as well as frustration by the students and faculty. Students often park in grass or rely on shuttles to pick them up from off-site locations. Our research tackles this problem using a prediction model to recommend unfilled parking garages at the time that they must arrive to campus. This will assist students in determining the best time to arrive at the parking garage, and help in policy for the University in setting classes to optimize the times that students classes start.

FIGURE 1. Map of campus with the garages **in green**. On a high level, a spatial assessment can be made to understand the location of the garages across campus.

## II. METHODS

The analysis provided in this deliverable was re-purposed from a photovoltaics python package located at https://github.com/slacgismo/solar-data-tools as the periodic nature found in photovoltaic performance is also found in garage capacity signals.

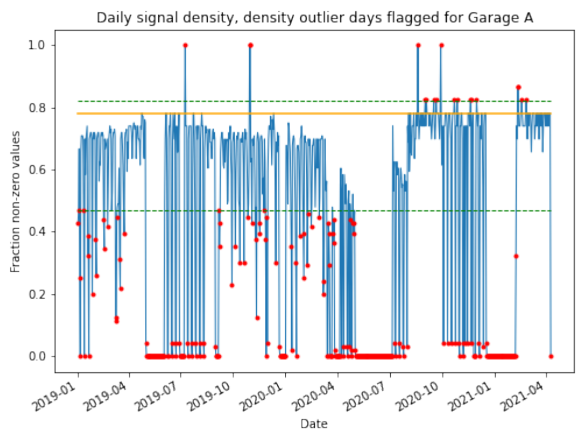


FIGURE 2. Detection of irregular times (i.e. nights, sensor outages, COVID implications, etc.) using an automated interval.

### A. PREPROCESSING

A preprocessing step is added to remove abnormal days from the dataset. In this study, we define abnormal days as ones with a small number of non-zero values. The preprocessing step was kept simple because we did not want to remove garage-specific characteristics. Some garages had many days filtered (A,C,D,H,I). A visualization is provided in Figure 2, and the rest of the garages are provided in the appendix in Figures A20 through A26.

### B. CAPACITY ANALYSIS

A parking garage capacity signal is measured at uniform intervals at each garage $G = ($"A","B","C","D","I","H","Libra"$)$. These garages are analyzed separately (i.e. independently) because of the unique profiles characteristic to each garage. Each garage has a capacity sensor which measures the percent capacity of the garage with a uniform one hour interval. During nominal periods, parking capacity is periodic; people arrive around 7 am every day and leave around 5 pm (Figures A6 - A12). Irregular periods (likely due to COVID or construction) show abnormal signals, characterized by non-daily-periodic tendencies. Sensor data is resampled and imputed (via linear interpolation) to produce a 15-minute sampling interval to allow smoother plots.

A matrix of the capacity data is constructed as

$$C = \begin{bmatrix} c_{1,1} & \dots & c_{1,d} \\ \dots & \ddots & \dots \\ c_{n,d} & \dots & c_{d,m} \end{bmatrix}$$

where a day $d$ has $n$ points that are usually arranged in a periodic pattern. The total number of points available from this sample is of size $n \times d$.

Instead of defining a busy capacity as being one greater than 95% (let's say), understanding whether a day is busier than normal would be hard to do. A consolidation of this data into a "busy-day" signal $c = g(t)$ defines busy levels as a function of time of day. This extra step likely allows for a more robust summarization of deviations from the busy day model, allowing for easier prediction.

Additionally, a model robust to data sparsity is required as covered by GLRMs.

A generalized low rank model [1] is constructed to summarize $D \approx LR$ where $L \in \mathbb{R}^{m \times k}$ and $R \in \mathbb{R}^{k \times n}$. The parking capacity is summarized by the $L$ and $R$ estimates under busy-day conditions. A busy day is defined as one with smooth, parabolic data across a day of data which has magnitudes similar to other busy days in the dataset. A regularization function adopted from [2] is utilized to minimize the $D$ construction loss. A function

$$f_1 = \phi_\tau((D - LR)(w))$$

helps gravitate the construction of teh busy-day model towards one with smooth signals. Additionally,

$$f_2 = \mu_L ||D_2 L||_F$$

helps push a construction towards a consistent busy-day model across multiple samples (days) in the data. Thirdly,

$$f_3 = \mu_R ||D_2 R^T||_F$$

to ensure a match with measured busy data. And lastly,

$$f_4 = \mu_R ||D_{1,365} \bar{R}^T||_F$$

is utilized when the number of days > 365 to observe a year-wise periodicity. The $L$ and $R$ matrices are initialized to the top five singular values as extrapolated from a singular value decomposition $D = U \Sigma V^T$ of the capacity signal. This is an essential step because the optimization algorithm which aids in the GLRM decomposition process is dependent on a reasonable initialization. Additionally, a penalty function $\phi_\tau(x)$ is generated to constrain the $L$ and $R$ decomposition to specifically center the predicted busy-day model in the first column of the $L$ matrix.

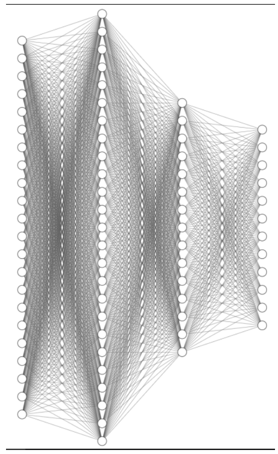

FIGURE 3. Neural network architecture of a simple multi-layer perceptron with dense layers and dropout layers.

### C. PARKING AVAILABILITY PREDICTION

Prediction of the garage capacity was done using a sequence to sequence neural network. The model selected was a simple regression model with an input of the first 44 data points for that day taken at 15 minute increments. The inputs were then fed into a fully connected layer with 50 neurons, followed by a fully connected layer with 15 neurons. Output of the network would be a vector of predictions on which parking garages would be open at the specified time.

The simple regression model was selected because it allowed for quick prototyping and training. Different activation functions such as relu, sigmoid, and softmax were used. The resulting networks were cross-validated with data from January and February of 2020.

## III. RESULTS AND DISCUSSION

A visual verification of the model is provided in the appendix. Figures A1 through A5 show, for each garage, the busy day model (in orange) compared to the measured signal. We detect busy times as shown in red. To reiterate from earlier in this document, our definition of busy times here are more bayesian-oriented: a busy status given a certain time. The busy-day daily profile can be observed to determine which garage is consistently free during your commute hours. Thus, a garage can easily be chosen. Instead of just being utilized individually, the university can help assign students to garages to distribute the parking demand in certain garages at certain times. This can have large time-saving ramifications for students and teachers, who often answered on surveys that it can take up to 20-30 minutes to find an open parking spot.

Data became very unreliable once covid started. Interestingly, through the utilization of a simple clustering algorithm, we were able to detect the utilization of stay-at-home policies. Expectantly, COVID-19 had a significant impact on parking; however, some garages began to fill up again after 3 months. Garage A which was used as a COVID-19 testing opened and would be at max capacity from open to close (Figure A6). Other garages continued their normal operation as well. Parking garages near high traffic areas show the return of students and faculty during the Summer 2020 semester. Parking garage H's location near housing and classroom buildings lead to its consistent use during the pandemic (Figure A17). The Libra garage saw a significant increase in the semester immediately after COVID shutdowns happened. Its location near the largest on-campus housing complexes also lead to it consistently being near capacity (Figure A19). Sparse data for parking garage B shows a dip in capacity then a quick return to campus but may be inaccurate (Figure A14). Garages far from classrooms and housing maintained consistently low usage throughout the period that data was collected (Figures A15-A16). Overall the data shows a significant drop in parking usage followed by a quick return of essential staff and students who needed to remain in on-campus housing. The full return to campus is planned for Fall 2021 and will cause significant issues with parking once again. Student who have not previously been to campus will learn that parking availability at UCF changes quickly. Our analysis of available data showed that parking garages fill up significantly in the 15 minutes leading up to class.

## REFERENCES

[1] M. Udell, C. Horn, R. Zadeh, and S. Boyd, "Generalized low rank models," arXiv preprint arXiv:1410.0342, 2014.
[2] B. Meyers, M. Tabone, and E. C. Kara, "Statistical clear sky fitting algorithm," arXiv preprint arXiv:1907.08279, 2019.

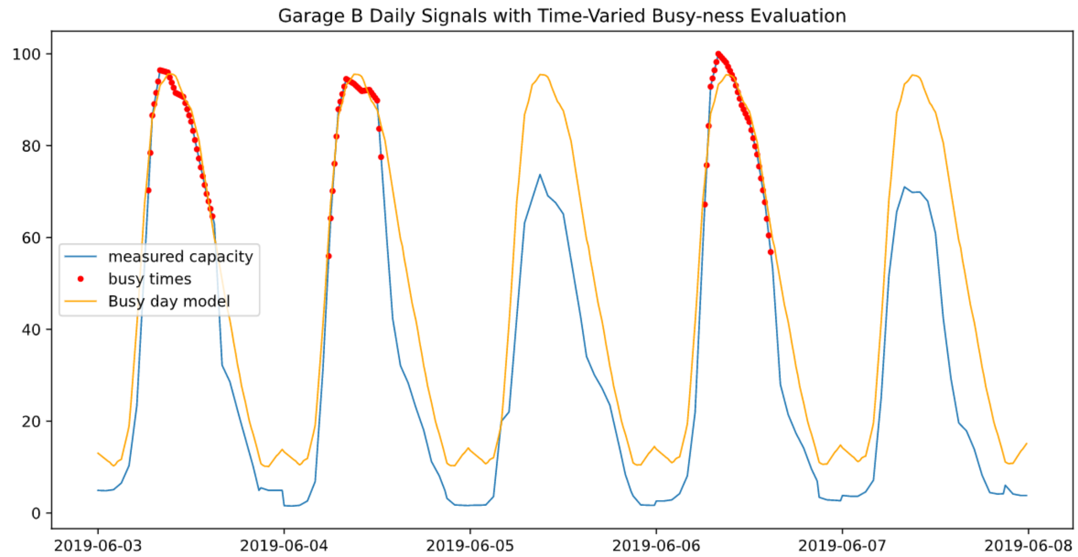


**FIGURE A1.** Measured garage capacity versus a busy-day baseline model estimated utilizing convex optimization (See Section II).

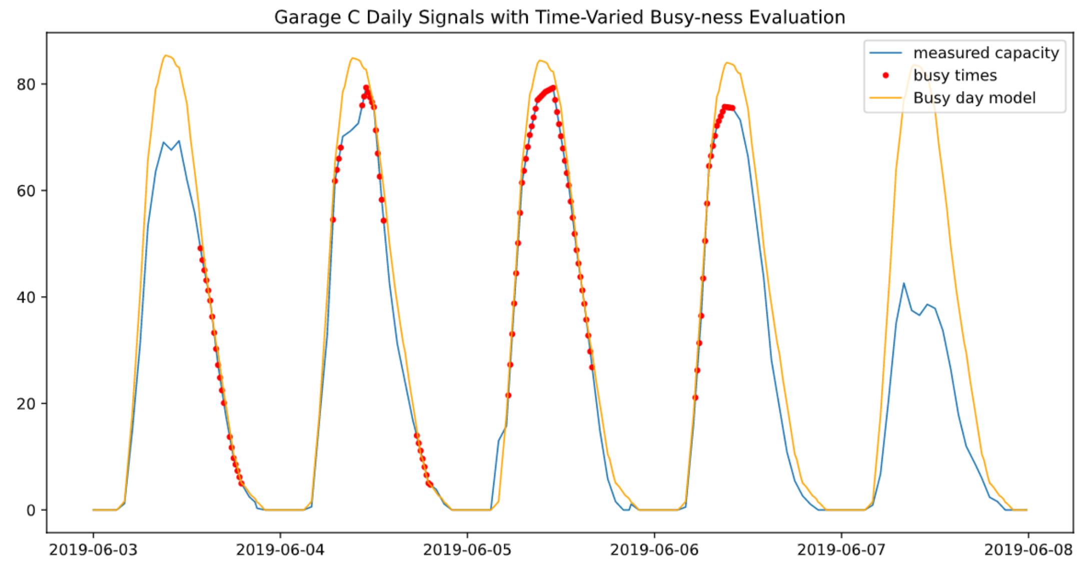


**FIGURE A2.** Measured garage capacity versus a busy-day baseline model estimated utilizing convex optimization (See Section II).

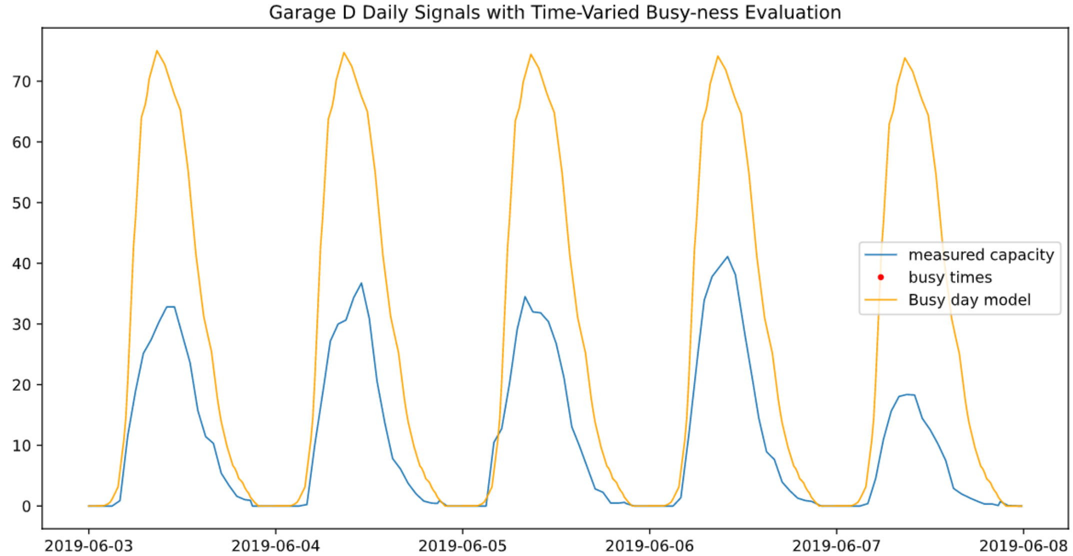


**FIGURE A3.** Measured garage capacity versus a busy-day baseline model estimated utilizing convex optimization (See Section II).

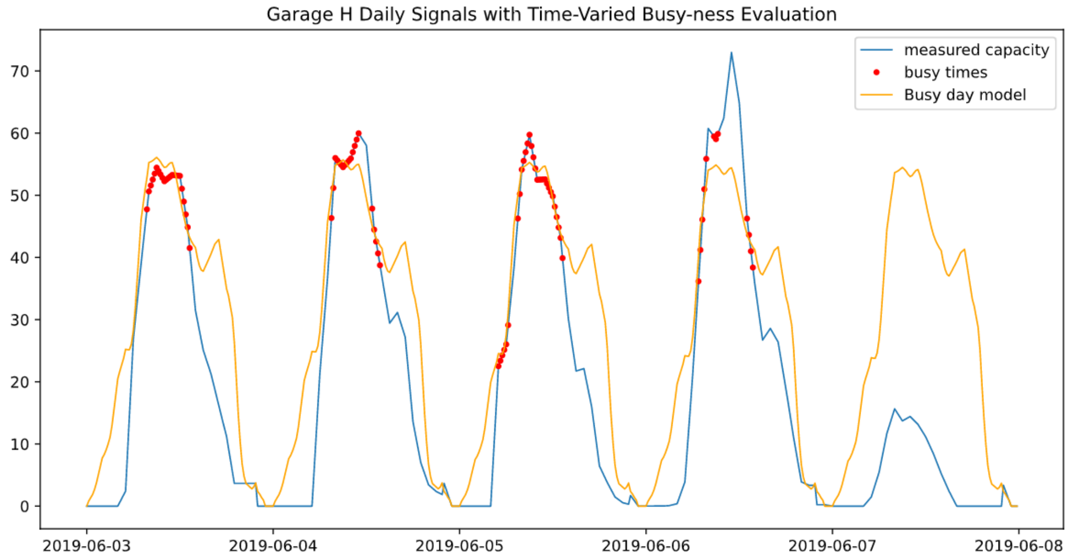


**FIGURE A4.** Measured garage capacity versus a busy-day baseline model estimated utilizing convex optimization (See Section II).

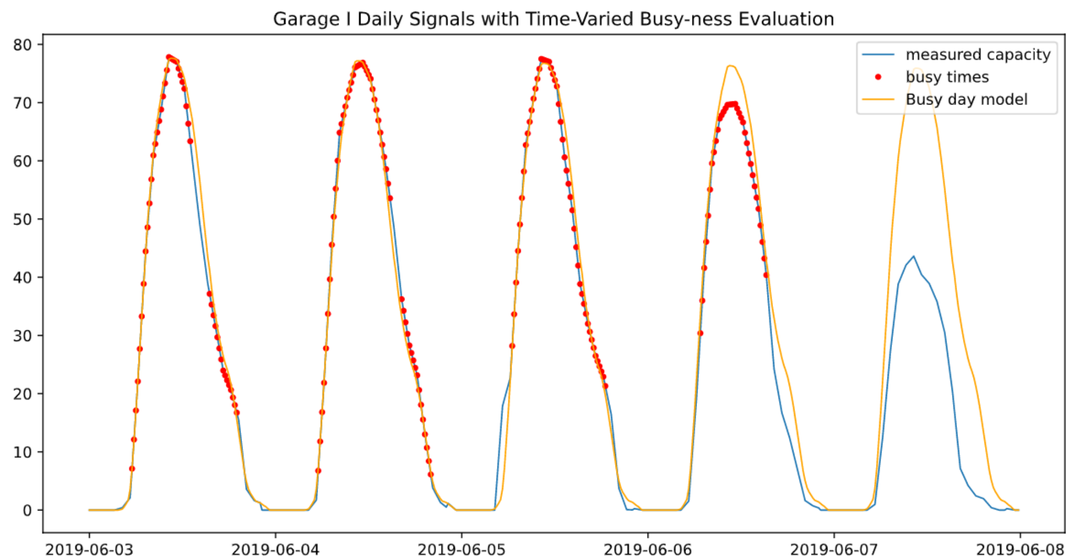


**FIGURE A5.** Measured garage capacity versus a busy-day baseline model estimated utilizing convex optimization (See Section II).

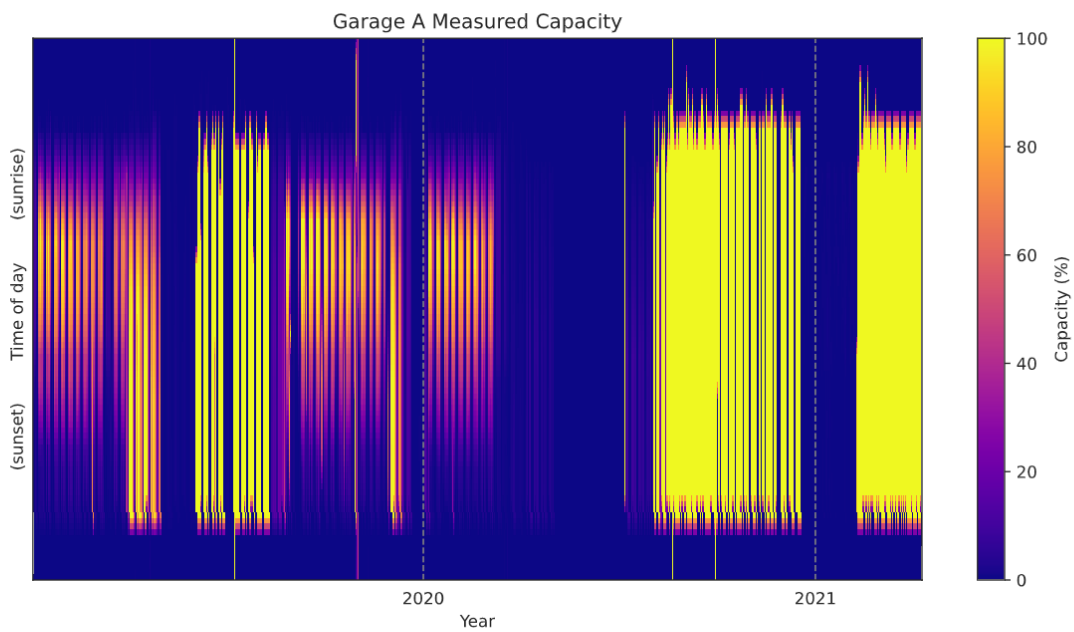


**FIGURE A6.** Heatmap of the capacity across time of day (y-axis) and days (x-axis) shows nominal periodic tendencies and abnormal tendencies as caused by the COVID19 pandemic.

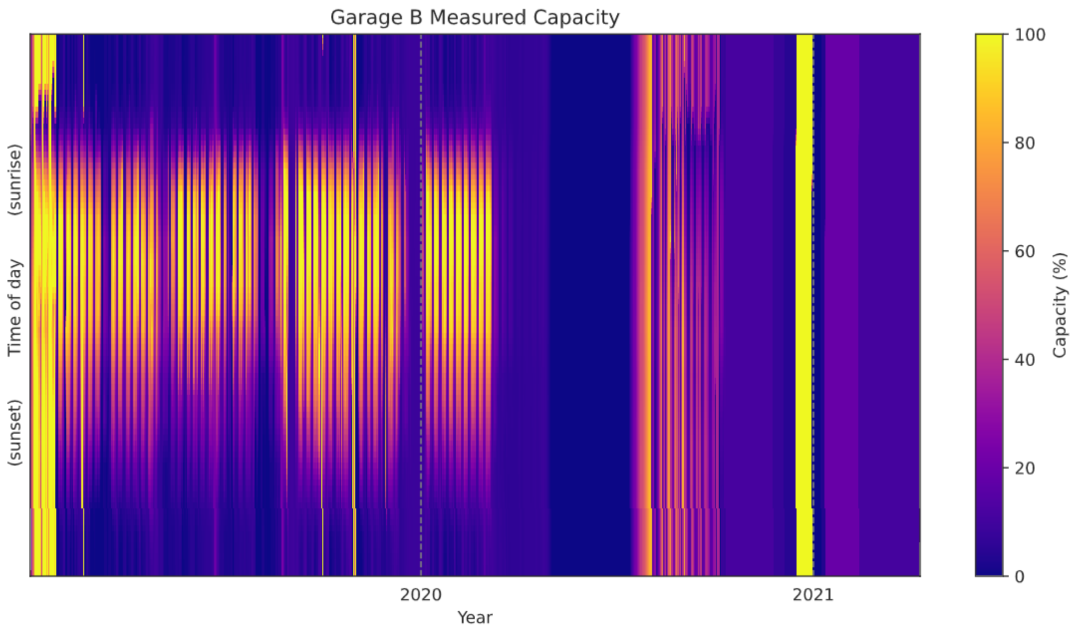


**FIGURE A7.** Heatmap of the capacity across time of day (y-axis) and days (x-axis) shows nominal periodic tendencies and abnormal tendencies as caused by the COVID19 pandemic.

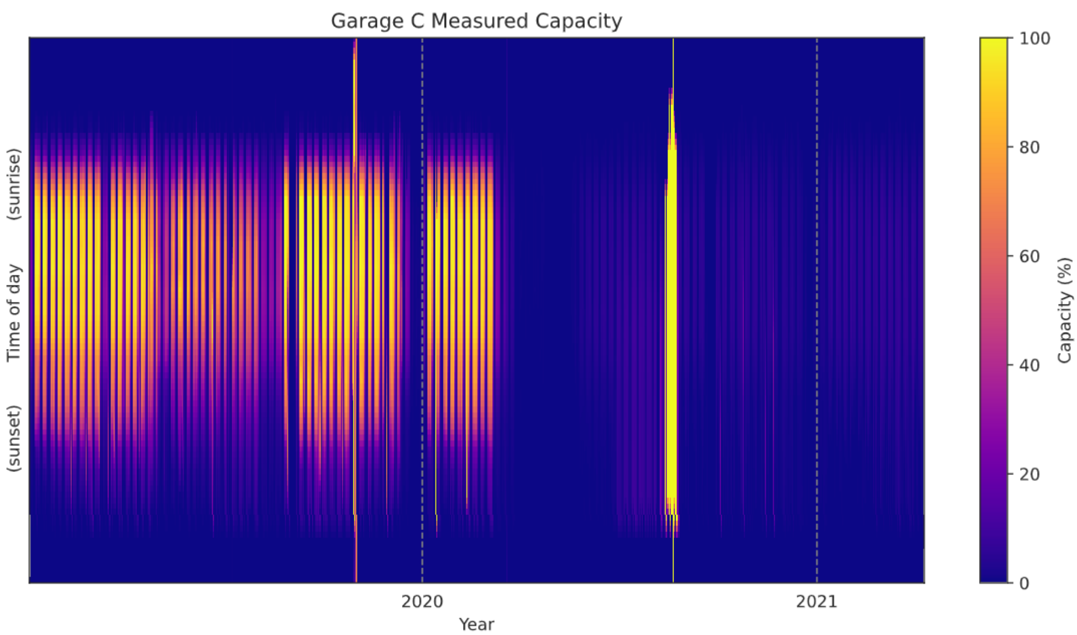


**FIGURE A8.** Heatmap of the capacity across time of day (y-axis) and days (x-axis) shows nominal periodic tendencies and abnormal tendencies as caused by the COVID19 pandemic.

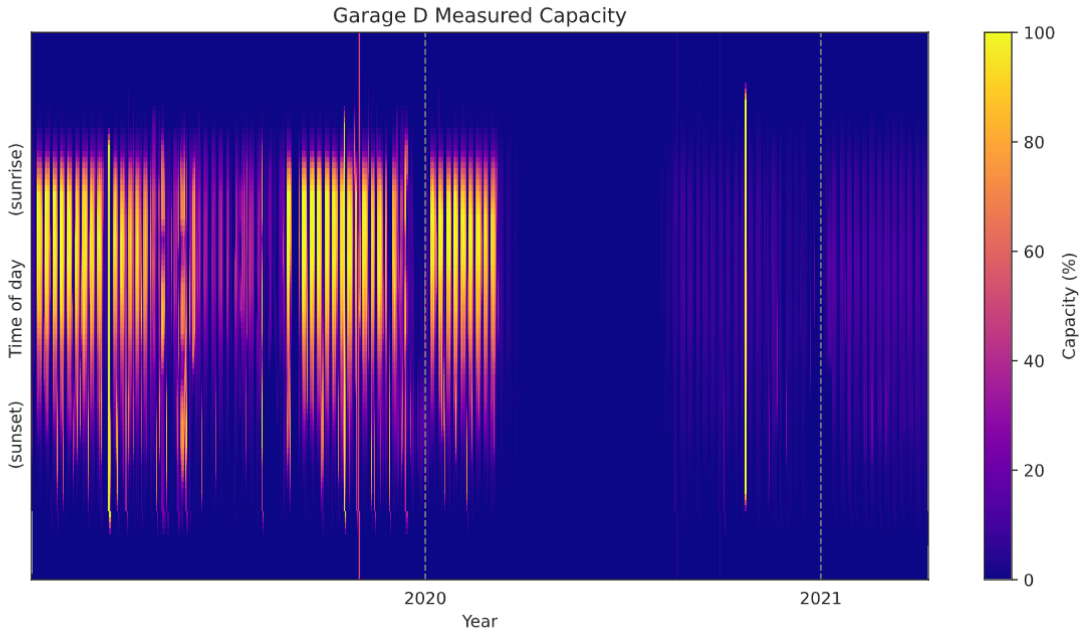


**FIGURE A9.** Heatmap of the capacity across time of day (y-axis) and days (x-axis) shows nominal periodic tendencies and abnormal tendencies as caused by the COVID19 pandemic.

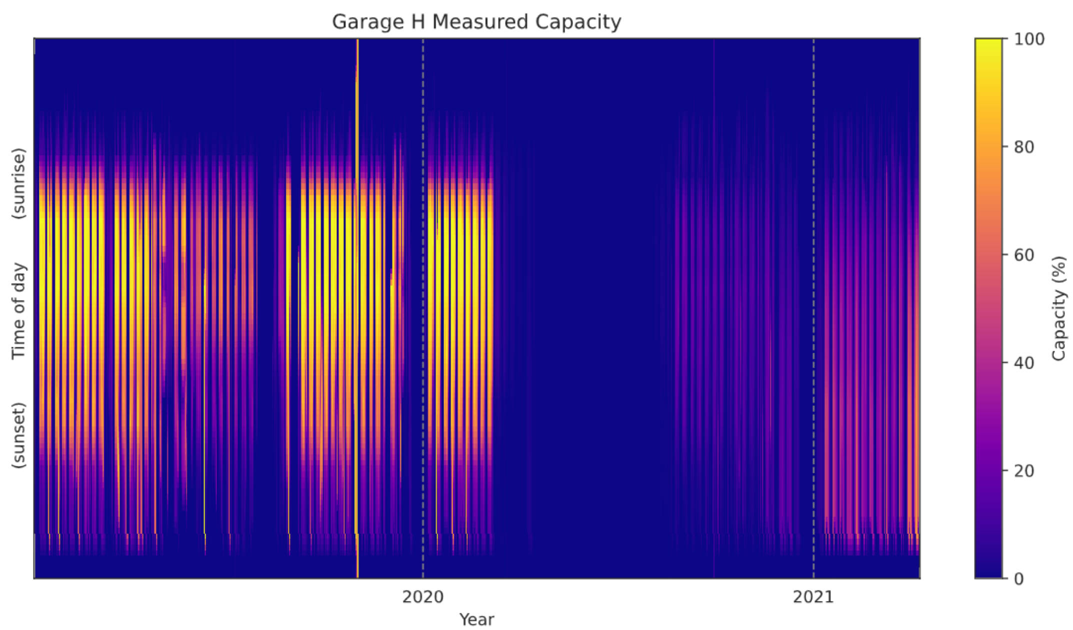


**FIGURE A10.** Heatmap of the capacity across time of day (y-axis) and days (x-axis) shows nominal periodic tendencies and abnormal tendencies as caused by the COVID19 pandemic.

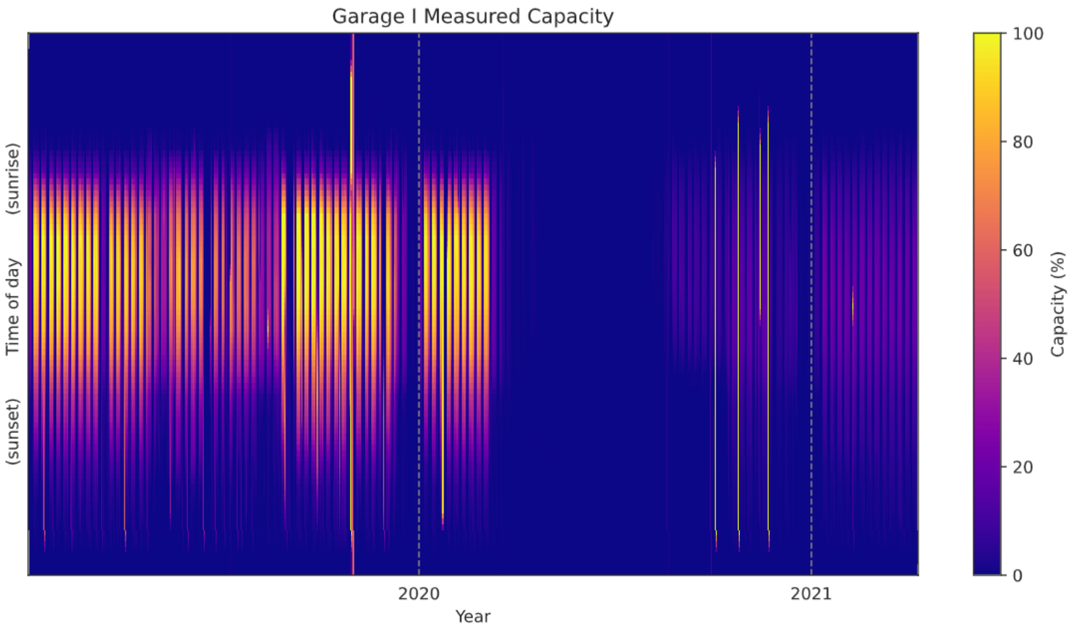


**FIGURE A11.** Heatmap of the capacity across time of day (y-axis) and days (x-axis) shows nominal periodic tendencies and abnormal tendencies as caused by the COVID19 pandemic.

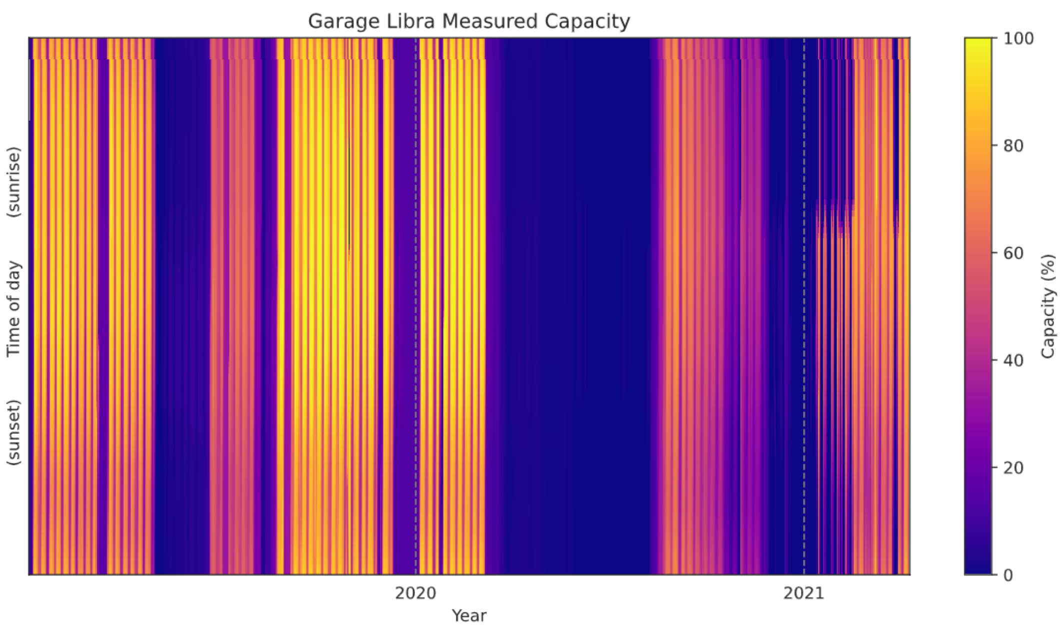


**FIGURE A12.** Heatmap of the capacity across time of day (y-axis) and days (x-axis) shows nominal periodic tendencies and abnormal tendencies as caused by the COVID19 pandemic.

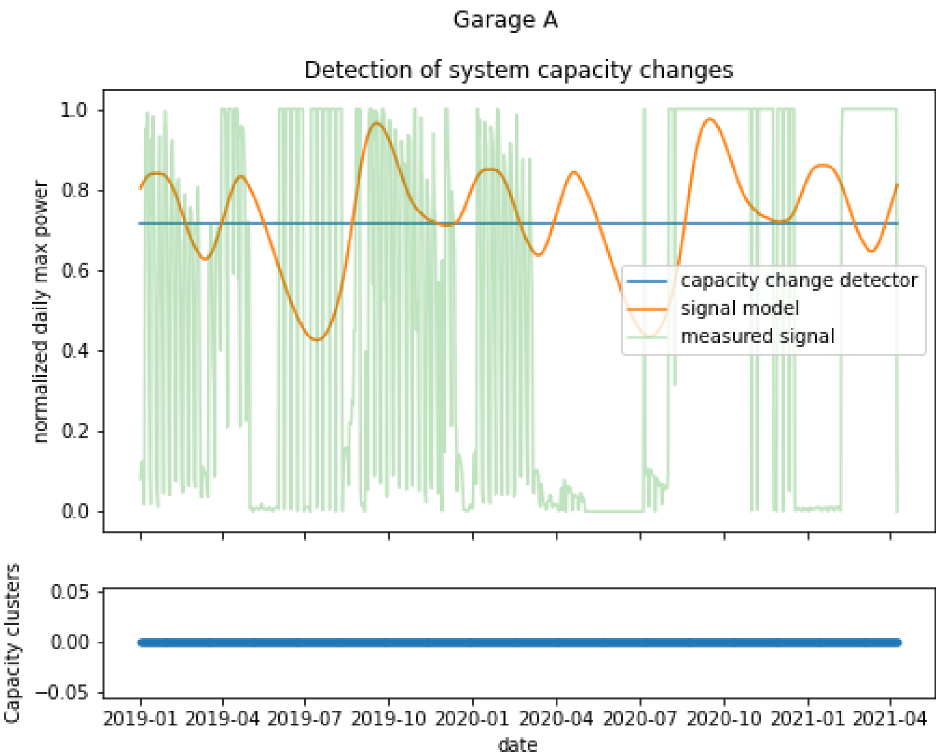


**FIGURE A13.** No significant capacity change likely due to COVID because this garage was used as a COVID testing site.

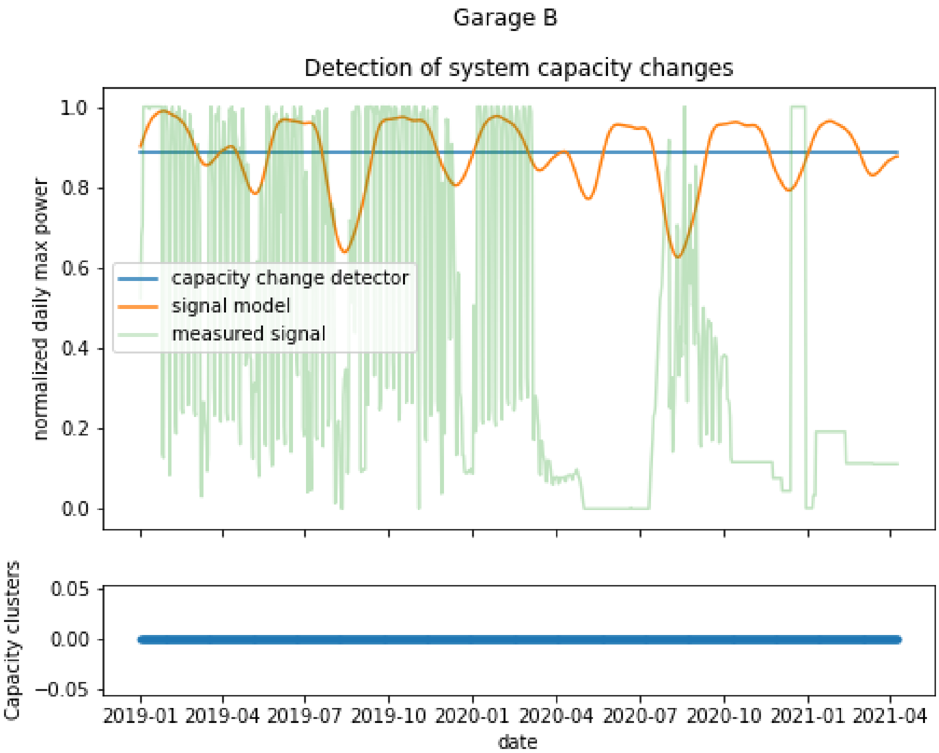


**FIGURE A14.** No significant capacity change was found due to COVID because this garage is near non-academic facilities.

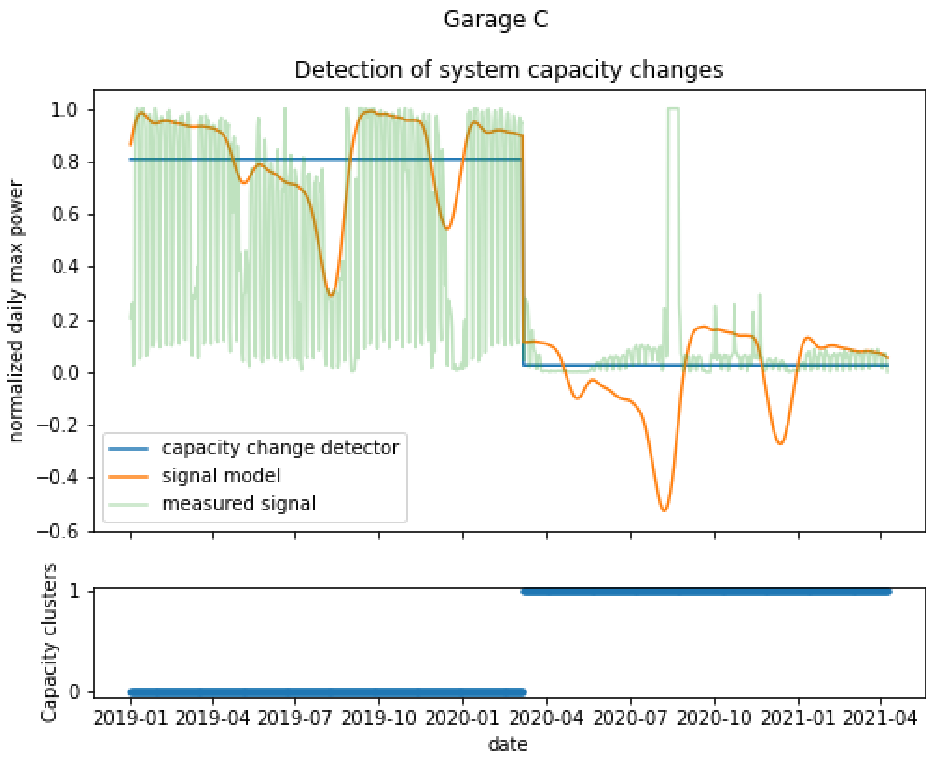


**FIGURE A15.** A significant change in parking capacity was found due to COVID.

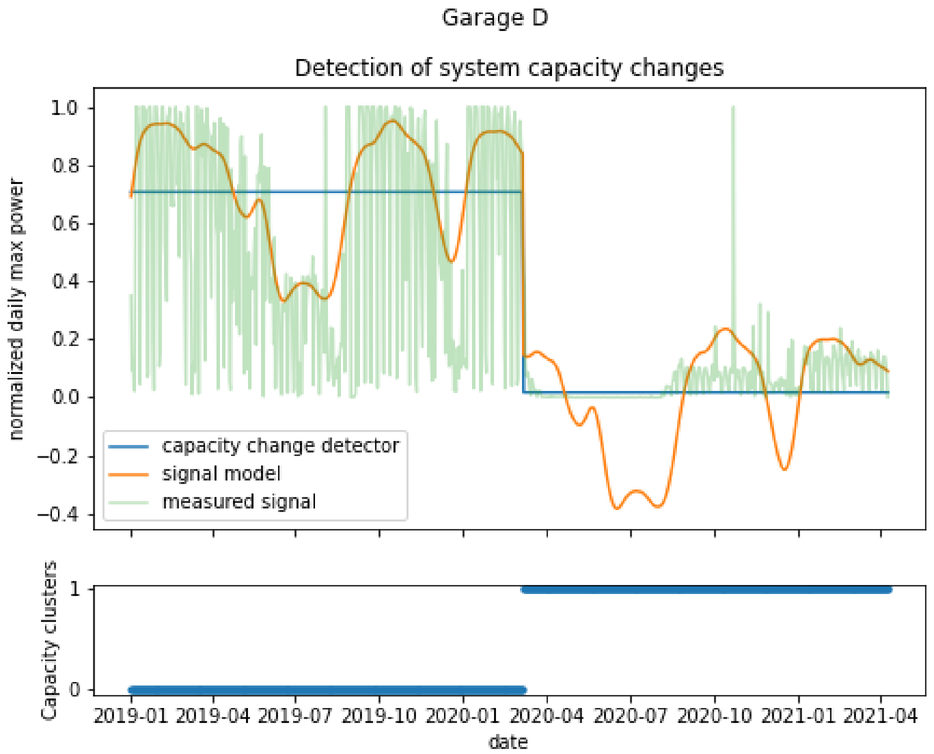


**FIGURE A16.** A significant change in parking capacity was found due to COVID.

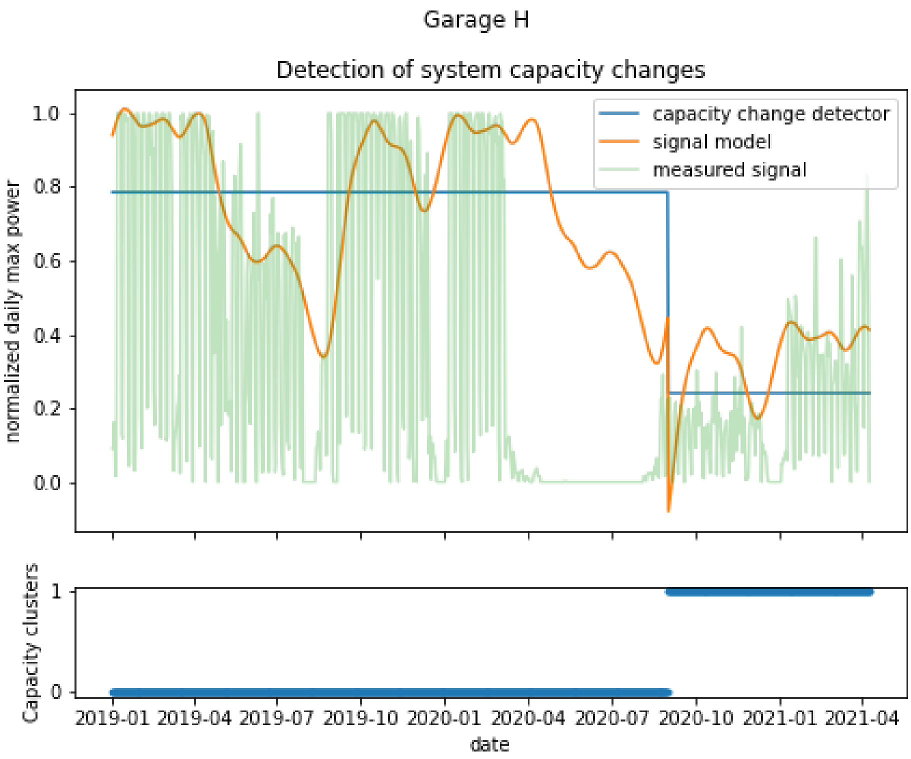


**FIGURE A17.** A significant change in parking capacity was found due to COVID.

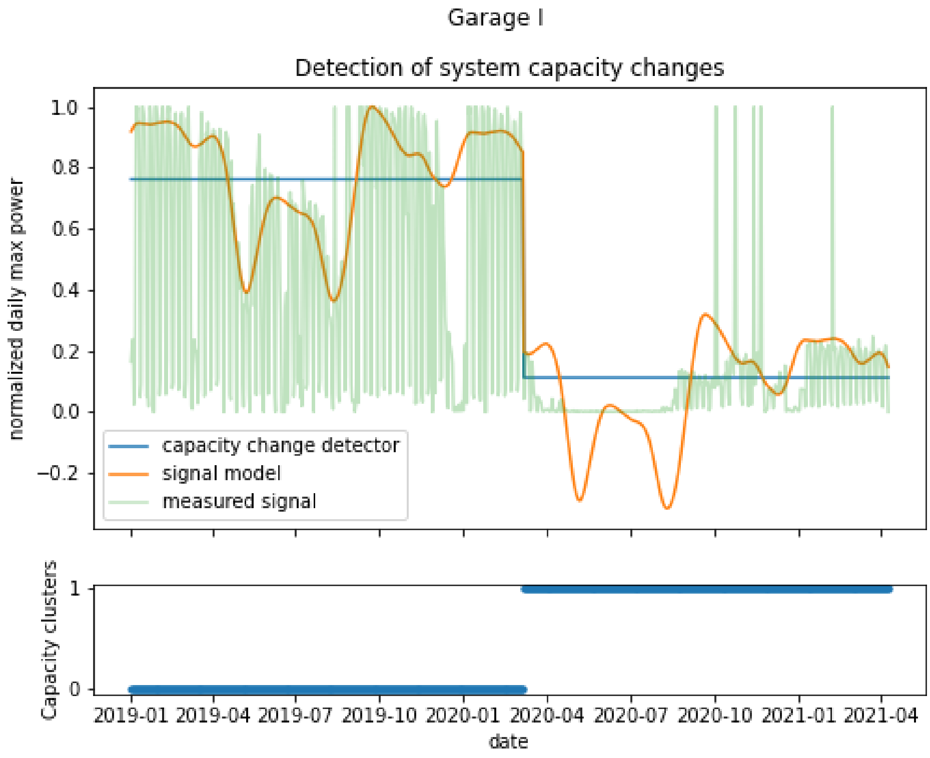


**FIGURE A18.** A significant change in parking capacity was found due to COVID.

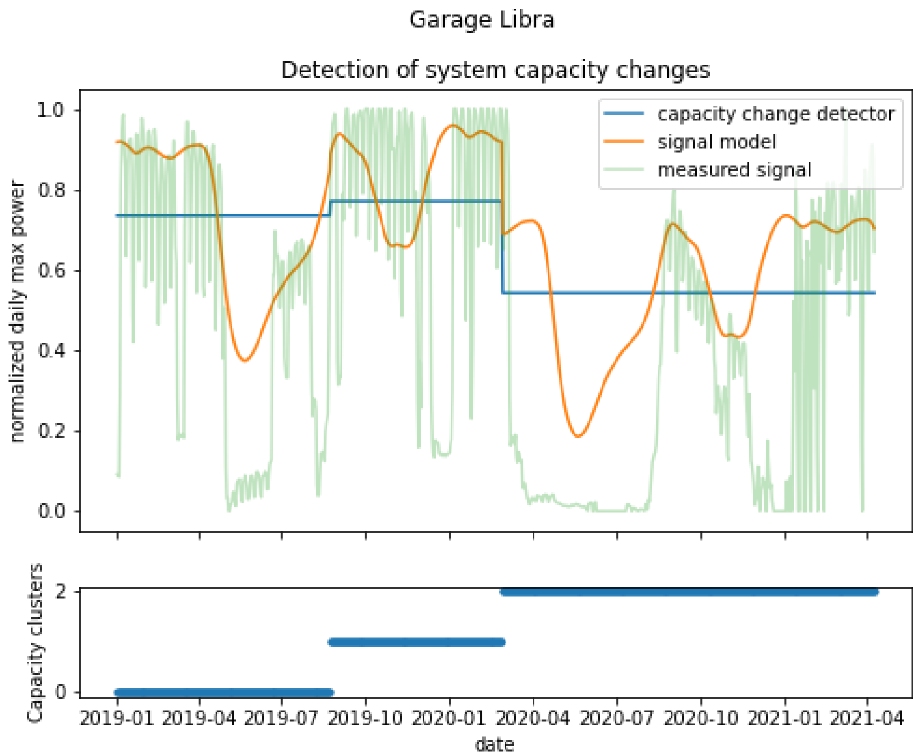


**FIGURE A19.** A significant change in parking capacity was found due to COVID.

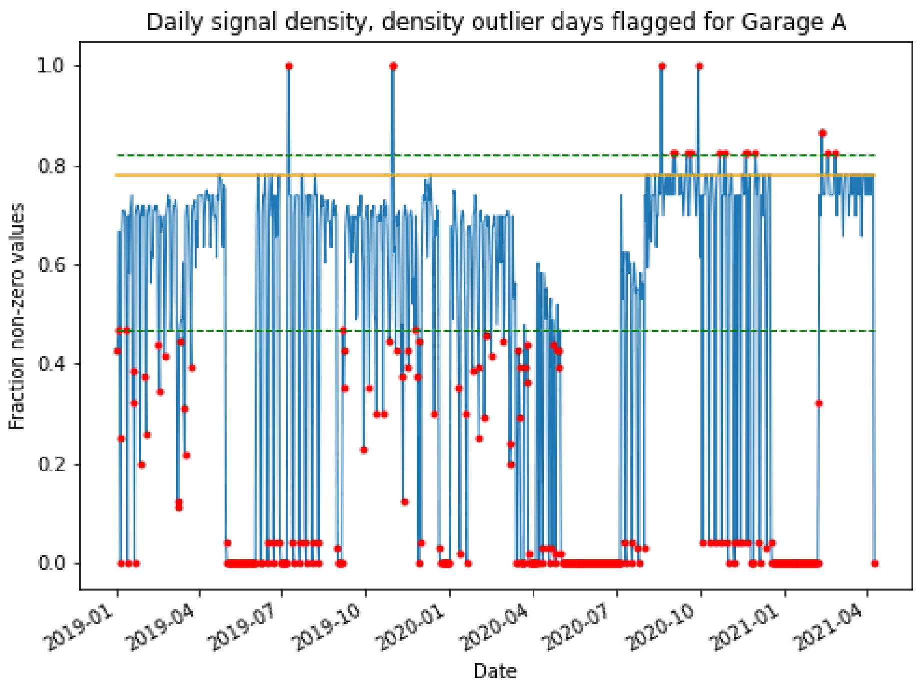


**FIGURE A20.** Detection of irregular times (i.e. nights, sensor outages, COVID implications, etc.) using an automated interval.

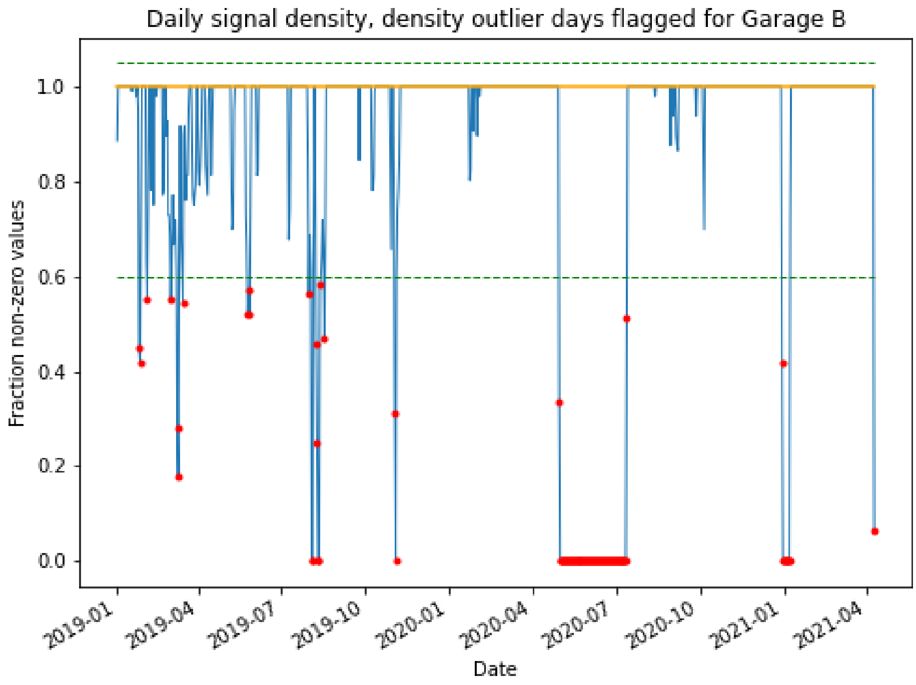


**FIGURE A21.** Detection of irregular times (i.e. nights, sensor outages, COVID implications, etc.) using an automated interval.

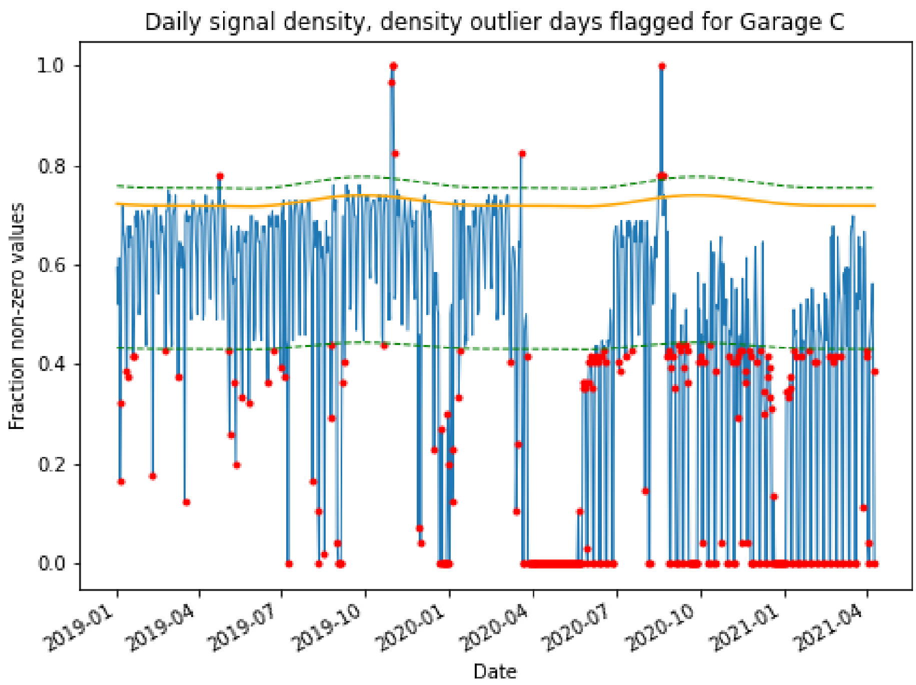


**FIGURE A22.** Detection of irregular times (i.e. nights, sensor outages, COVID implications, etc.) using an automated interval.

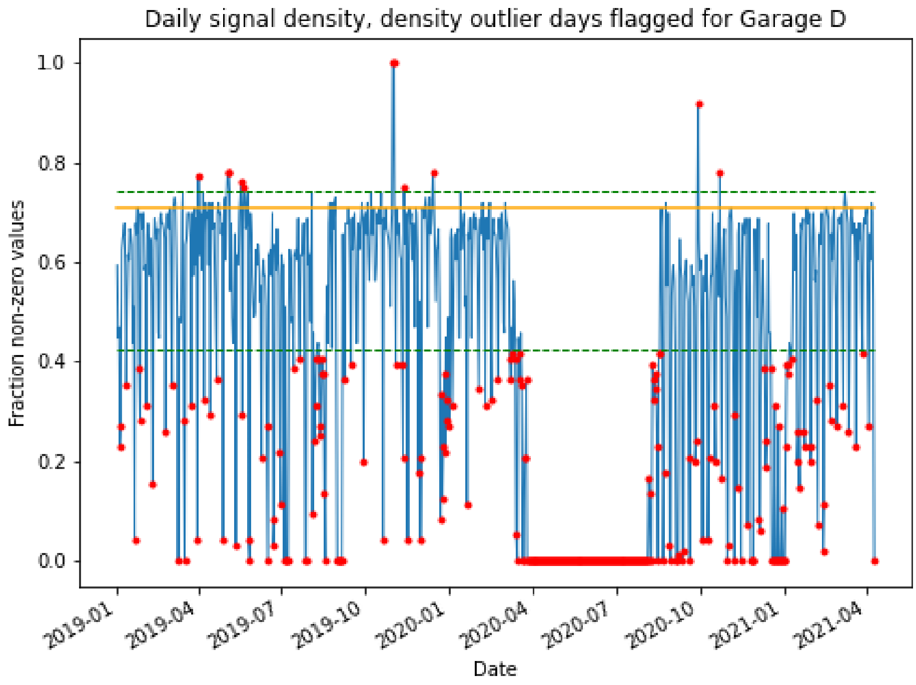


**FIGURE A23.** Detection of irregular times (i.e. nights, sensor outages, COVID implications, etc.) using an automated interval.

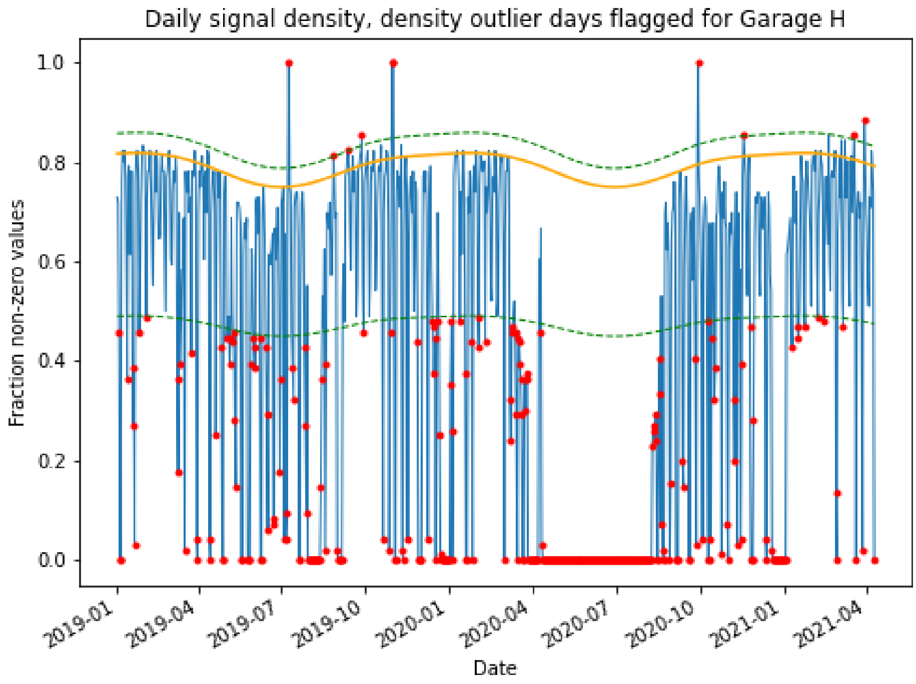


**FIGURE A24.** Detection of irregular times (i.e. nights, sensor outages, COVID implications, etc.) using an automated interval.

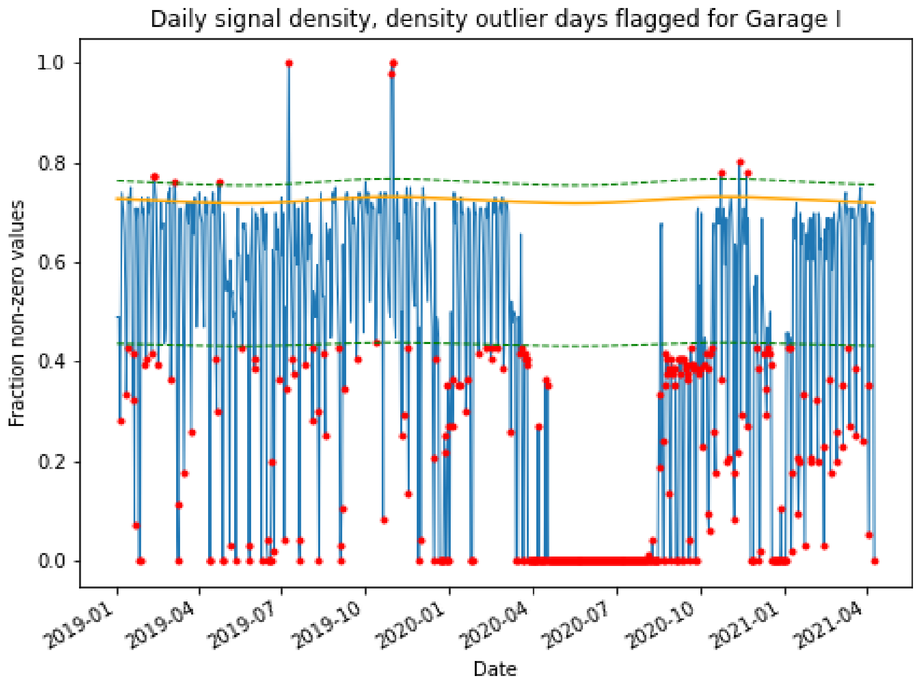


**FIGURE A25.** Detection of irregular times (i.e. nights, sensor outages, COVID implications, etc.) using an automated interval.

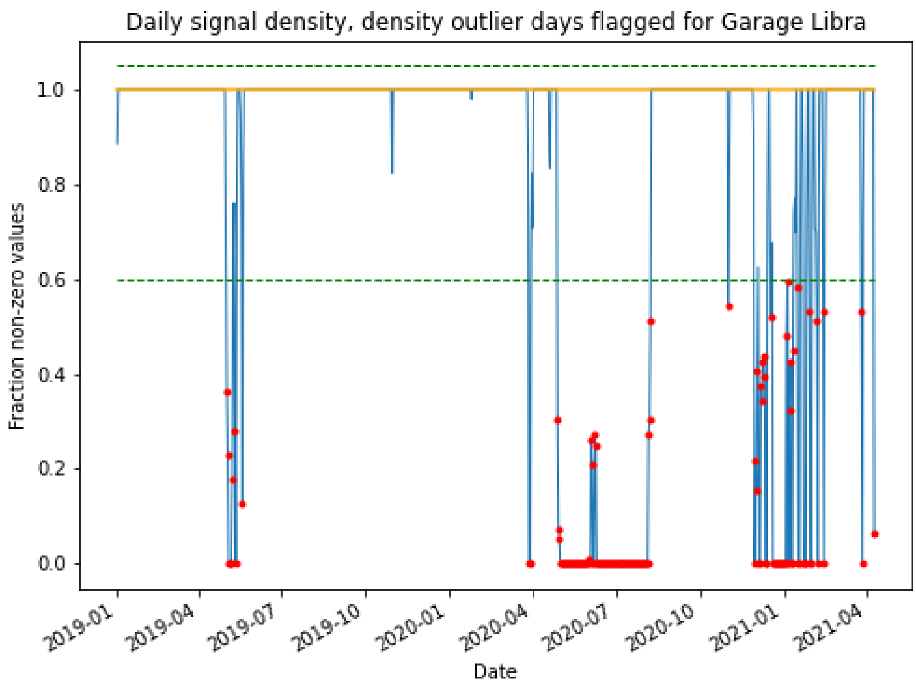


**FIGURE A26.** Detection of irregular times (i.e. nights, sensor outages, COVID implications, etc.) using an automated interval.