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Stretching Rubber, Not Budgets: Accurate Parking Utilization on a Shoestring

Abstract

Effective parking management is essential for ensuring accessibility, safety, and convenience in master-planned communities, particularly in active adult neighborhoods experiencing rapid growth. Accurately assessing parking utilization is a crucial first step in planning for future demand, but data collection methods can be costly and labor-intensive. This paper presents a low-cost yet highly accurate methodology for measuring parking utilization using road tubes connected to portable traffic counters from JAMAR Technologies, Inc. By integrating results from JAMAR's analysis tool with custom Python scripting, the methodology enables precise parking lot counts through parameter optimization and automated error correction. The system's efficiency allows for scalable deployment without significant manual observation, reducing both costs and disruptions to daily operations. Using Tellico Village as a case study, this research demonstrates that community planners can obtain actionable parking insights on a limited budget, empowering them to make informed decisions about capacity expansion, traffic flow improvements, and facility scheduling. The findings underscore the feasibility of leveraging cost-effective technology to optimize infrastructure planning and ensure long-term resident satisfaction as communities grow.

1. Introduction

Adequate parking is a cornerstone of master-planned communities, particularly in active adult lifestyle neighborhoods experiencing significant population growth. Sufficient parking ensures safety, convenience, and accessibility for residents and visitors, while also minimizing congestion and supporting local businesses. A proactive approach to parking management begins with measuring lot utilization to gain insights into both existing demand and future needs. This data empowers community and facility managers to predict peak usage as the community nears buildout, enabling them to take corrective action—such as expanding lot capacity, improving traffic flow, or adjusting facility schedules—before parking shortages become a real problem. By addressing potential issues early, managers can ensure seamless operations and sustained resident satisfaction.

2. Tellico Village Parking Study

The case study for this work focuses on Tellico Village, an active adult lifestyle community with more than 5,800 homes located in East Tennessee. As the population of Tellico Village continued to grow, residents and guests began encountering parking congestion at various facilities. At the request of the

Property Owners Association (POA) Board of Directors, the Long-Range Planning Advisory Committee (LRPAC) conducted a study to assess the scope of the problem.

In April 2024, the LRPAC conducted a brief survey to identify which facilities were most affected. Responses from over 1,100 residents revealed that the average percentage of time residents reported having “difficulty finding a parking space” was highest at the Wellness Center (14%), Toqua Bar & Grill (19%), Chota Recreation Center (28%), and the Yacht Club (29%). Although the survey was not designed to uncover the full extent of parking issues, the data indicated that 12-14% of respondents experienced parking difficulties at least three times per month.

Based on these findings, the decision was made to collect more detailed data to determine whether parking capacity at the four facilities was sufficient to meet current and future demand. Specifically, utilization measurements of each parking lot would enable the LRPAC to:

- a) Assess the severity, timing, and duration of parking under-capacity, and
- b) Estimate capacity requirements through buildout [1].

The estimate for (b) is agnostic, as overutilization can be addressed by either increasing capacity (adding parking spaces to meet demand), reducing peak demand (incentivizing vehicles to arrive at other times), or a combination of both approaches.

3. Seasonality of Demand

To ensure the collected data would be actionable, the days chosen to measure parking utilization needed to represent “typically busy” days rather than holidays or special-event days, which attract the most visitors but occur infrequently. Previous studies of visitor attendance at these facilities indicated that certain months experienced the highest average demand. Consequently, parking lot measurements were conducted only during those months. Instead of attempting to predict the specific days with the highest congestion, parking demand for each lot was measured continuously over one or more months, with the measurement period divided into multiple counts lasting approximately one week each.

Once all the counts for a parking lot were completed, the day(s) with the highest utilization from each count were selected for comparison across counts. The comparison metrics used to determine “highest utilization” are described in Section 12.

4. Measurement Method

The LRPAC researched various vehicle counting methods that utilized different sensor technologies. Based on the project’s goals, timeframe, and resources, the options were narrowed down using the following selection criteria: ease of deployment and data processing; ability to collect data continuously (24/7) over extended periods and in all weather conditions; capability to distinguish between cars and golf carts; ability to monitor multiple lots simultaneously; extendibility to other use cases; and cost-effectiveness for purchase and maintenance. Ultimately, portable traffic counters utilizing road tubes were selected as the measurement method, as they were the only option that satisfied all the criteria.

The Tellico Village POA purchased a traffic recording system designed and manufactured by JAMAR Technologies, Inc., based in Hatfield, PA. The system included two portable TRAX Pinnacle traffic

counters [2], a single-use license for STARnext [3] (JAMAR’s analysis software for processing traffic data), and road tubes with fixtures for installation.

5. Measurement, Analysis and Post-Processing

Figure 1 illustrates the essential elements of the measurement process, which are explained below.

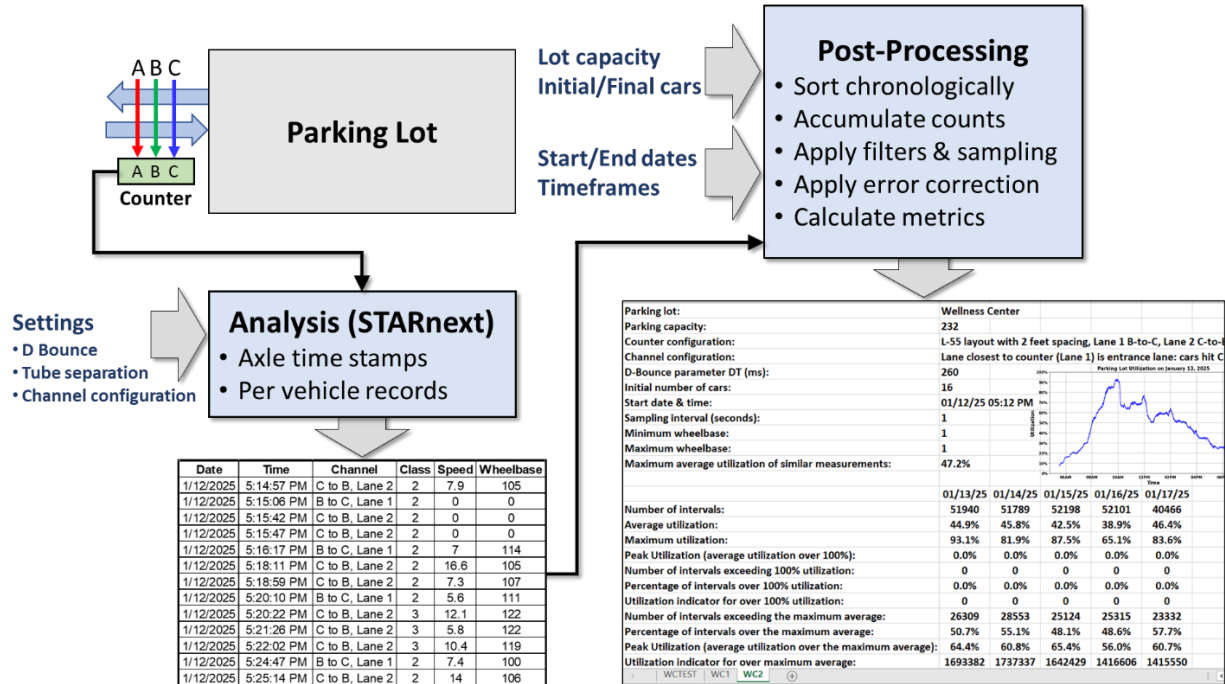


Figure 1. The measurement of parking utilization involved three major steps: detection, analysis, and post-processing.

Detection. When a vehicle’s tires pass over a set of tubes, air pressure waves travel through the tubes to the traffic counter. The counter senses these pulses, converts them into electrical signals, and processes the pulse sequence to identify a detected vehicle. This information is stored in memory as an axle timestamp along with related data for counting and subsequent analysis. Two counters are required when there are two separate entrances to a parking lot.

Analysis. Once the data from a count is transferred from the traffic counter to the STARnext analysis software, various computations are automatically performed based on user-controlled parameter settings. The primary objective of this step is to produce a set of axle timestamps that ensures the most accurate vehicle count. After this is achieved, a “golden” Excel worksheet is generated for the count. The worksheet contains columns for each detected vehicle, including the date, time, direction of travel (entry into or exit from the lot), and other per-vehicle details such as estimated speed, wheelbase length, and vehicle class. In cases where two counters are used, an independent analysis is performed for each count.

Post-Processing. This step, implemented in Python, processes the per-vehicle traffic data from the Excel worksheet(s) to produce an accurate utilization estimate for each day of the count. It combines data from multiple counters (if applicable), sorts the per-vehicle data chronologically, accumulates counts, applies filters and error correction, and calculates various utilization metrics. An Excel worksheet is

generated with separate sheets for each count, each including daily summary statistics. Additionally, plots are created to visualize daily utilization patterns over time.

6. Tube Configuration

For the most accurate results, the STARnext software requires data from a minimum of two tubes to estimate a vehicle's speed and wheelbase length. These estimations are based on the distance between the tubes – typically 2 feet – and the timing of the activation pulses they generate. The counter has four channels with input ports labeled A, B, C, and D that can be connected to up to four tubes. By convention, the lane closest to the counter is designated as Lane 1. Vehicles traveling in Lane 1 pass over the A tube (connected to the A channel) first, followed by the B tube (A → B). Vehicles in the opposite lane, Lane 2, approach the B tube first (B → A).

Distinguishing between vehicles entering and exiting a parking lot is essential. To maintain consistency across all measurements, we configured STARnext to assign Lane 1 for vehicles entering a lot and Lane 2 for vehicles exiting, as illustrated in Figure 2.

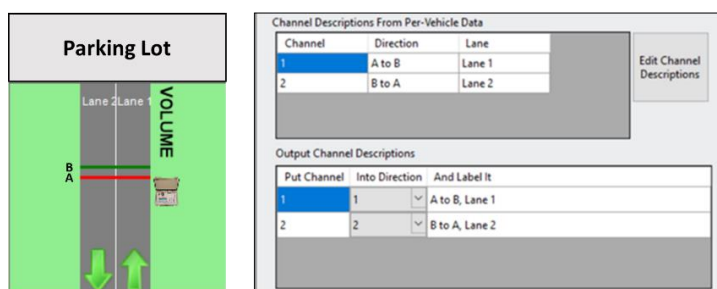


Figure 2. *Left:* The STARnext sensor layout showing two tubes connected to the A and B channels. Vehicles entering the parking lot use Lane 1. *Right:* Channel descriptions ensure correct directionality during post-processing by assigning the A → B direction to Lane 1 and the B → A direction to Lane 2.

A third tube (C) was added to provide fault tolerance in case one of the tubes becomes damaged during a count. STARnext supports the creation of custom sensor layouts to process data from any two channels independently. For example, if the A tube fails, a layout configuration that uses the B and C channels can be specified, allowing STARnext to calculate timestamp data using those channels.

If the B tube is damaged early in a count—such as what happened on one occasion at the Wellness Center parking lot—the count can still be salvaged by reconfiguring the sensor layout in STARnext to process data from the A and C channels. In this special case, the tube separation setting in STARnext had to be increased to 4 feet to reflect the physical distance between the undamaged A and C tubes.

Efforts should be made to eliminate counting errors that could compromise the accuracy of a count. Adhering to best practices when setting up road tubes—such as ensuring uniform spacing, maintaining proper tension, and cutting tubes to equal lengths—helps minimize the number of unclassified pulses in the dataset. In addition to these considerations, we applied innovative error minimization and correction techniques to achieve highly accurate estimates of parking lot demand, even in the presence of systemic detection errors. The following five sections detail the methods employed to achieve this.

7. Calculating Parking Demand

Once the channel configuration and tube separation settings are specified in STARnext, we fine-tune the vehicle count by comparing the predicted parking demand with the observed parking demand at the end of the count. Before describing this fine-tuning process, we will first explain how parking demand is calculated during the post-processing step.

We partition a count into N sampling intervals of equal duration T , expressed in seconds or minutes, and determine the number of timestamps recorded for each direction in each interval i . Predicted parking lot demand $D(n)$ represents the estimated number of vehicles in a parking lot after n sampling intervals. Alternatively, D can be described as a function of time t , where t is an integer multiple n of the sampling interval: $t = nT$. The value $D(t)$ is calculated as the initial observed number of vehicles, $D(t = 0)$, plus the cumulative difference between the number of vehicles entering and exiting the lot over all intervals up to n :

$$(1) \quad D(t) = D(nT) = D(t = 0) + \sum_{i=1}^n [\text{enter}(iT) - \text{exit}(iT)] \quad n \in 1, 2, \dots, N$$

Here, $\text{enter}(i)$ and $\text{exit}(i)$ are the numbers of vehicles entering or exiting the lot during sampling interval i . The precision of $D(t)$ depends on the duration of the sampling interval, with the minimum being $T = 1$ second, equivalent to the timing resolution of the counter.

Sampling intervals of 15 minutes or more are useful for simulating the effects of demand smoothing. For instance, one-hour fitness classes that allocate a fixed amount of time at the beginning of each hour for attendees to arrive and depart help mitigate large spikes in parking demand by spreading usage over the interval.

Predicted demand for a lot with two entrances is calculated as the sum of the cumulative differences between vehicles entering and exiting at each entrance. In practice, the calculation is applied using Equation (1) after combining the timestamp data from both counters into a single, chronologically ordered data frame.

8. Fine-Tuning Vehicle Count

The Dead Time (DT), also referred to as “D Bounce,” defines the duration the air switch in the TRAX Pinnacle counter waits after detecting a pulse before processing another. If the counter’s D Bounce setting is suboptimal, extraneous pulses caused by reverberations in the road tube will be recorded as additional vehicles. These undesirable pulses can result from several phenomena. For instance, vehicles entering and exiting a parking lot may cross the tube system simultaneously, creating signal cross-talk that generates false positives. Additionally, a slow-moving vehicle crossing a tube at an angle may cause the left and right tires to pass over the tube fractions of a second apart, producing extra pulses. By adjusting the D Bounce setting in STARnext, users can override the setting applied during the count to improve the accuracy of the recorded data.

In addition to changing the D Bounce setting, vehicles with wheelbase lengths outside a specific range can be excluded from a count in the post-processing step. STARnext assigns a wheelbase length of zero

if it cannot determine a vehicle's speed and wheelbase length, so it is important not to filter out these vehicles unintentionally.

The fine-tuning process for achieving highly accurate parking demand estimates involves selecting values for the D Bounce time (d) and the wheelbase length range (w) that minimize the difference between the predicted and observed number of vehicles in the lot at the end of a count. This process, aimed at minimizing the cumulative error of a count, is represented symbolically as:

$$(2) \min_{d,w} |D(N) - \Delta(N)|$$

where N again represents the total number of sampling intervals in the count, and $D(N)$ and $\Delta(N)$ denote the predicted and observed values at the last interval, respectively.

9. Removing False Positives

While the parameter optimization process described in the previous section worked well for almost all the counts, a rare case required additional steps to narrow the gap between predicted and observed demand. For example, as mentioned in Section 6, the separation distance between the tubes had to be increased to 4 feet to salvage a count due to a fault in the B tube. This adjustment led to a significant difference between $D(N)$ and $\Delta(N)$.

On the busiest day of the count, Day 2, we observed double counting under specific conditions: low vehicle speeds (mean ~ 2.3 MPH, often 0), short gaps between vehicles (mean ~ 7.3 feet, minimum ~ 2.6 feet), very short headways (mean ~ 7 seconds, minimum ~ 0.2 seconds), and cases where the wheelbase length was unknown (assigned a value of zero). Removing the false positives directly in the Excel worksheet significantly reduced the discrepancy between observed and predicted demand, narrowing the difference to just one vehicle at the end of the count. Figure 3 illustrates the predicted parking demand on Day 2, comparing the results before and after removing double counts.

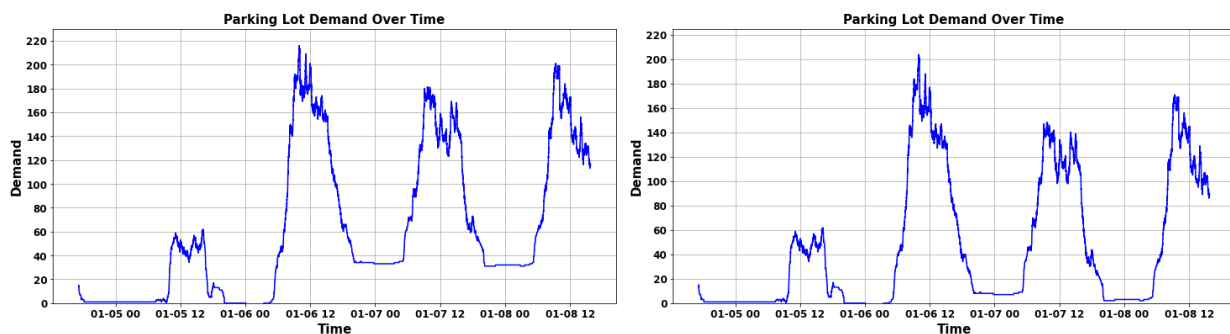


Figure 3. The chart on the left highlights the severe impact of double counting, with over 30 vehicles erroneously predicted to remain in the lot at the end of Day 2 instead of the expected zero. The chart on the right demonstrates improved accuracy after eliminating most of the false positives.

10. Applying Error Correction

The fine-tuning methods described above cannot guarantee the elimination of all errors, as varying traffic and weather conditions can introduce inaccuracies at different times and rates during a multi-day count. However, in most cases, it is possible to virtually eliminate the *average daily error*, meaning the cumulative error for each day.

Let σ_j represent the cumulative error by the end of the j th full day of the count. This is the difference between the predicted demand D_j and the ground truth demand Δ_j :

$$(3) \quad \sigma_j = D_j - \Delta_j$$

The average daily error (ε_j) is the error carried over from Day $j - 1$ to Day j . This is the difference between the cumulative errors:

$$(4) \quad \varepsilon_j = \sigma_j - \sigma_{j-1} = (D_j - \Delta_j) - (D_{j-1} - \Delta_{j-1})$$

with initial condition $\varepsilon_0 = D_0 - \Delta_0$, which is the error from the initial, partially measured day (Day 0).

Now let M represent the number of full days in the count. If we sum *all* daily errors, including the error from Day 0, all error terms up through Day $M - 1$ cancel out:

$$(5) \quad \sum_{j=0}^M \varepsilon_j = D_M - \Delta_M = D(N) - \Delta(N)$$

This equality confirms our intuitive notion that the sum of the average daily errors is equivalent to the cumulative error of the full count. Although the daily errors vary from day to day, as long as the predicted demand does not continue to increase or decrease monotonically over the count, accuracy can be further improved by introducing a “phantom” demand adjustment equal and opposite to each daily error ε_j , as defined in Equation (4).

If the end-of-day time is selected to be very early in the morning of the following day, the ground truth demand at that time is likely to be zero for some parking lots, in which case the demand adjustment required to negate each daily error simplifies to:

$$(6) \quad -\varepsilon_j = -(D_j - D_{j-1}), \quad 1 \leq j \leq M$$

Figure 4 illustrates the predicted demand for one day, both before and after error correction.

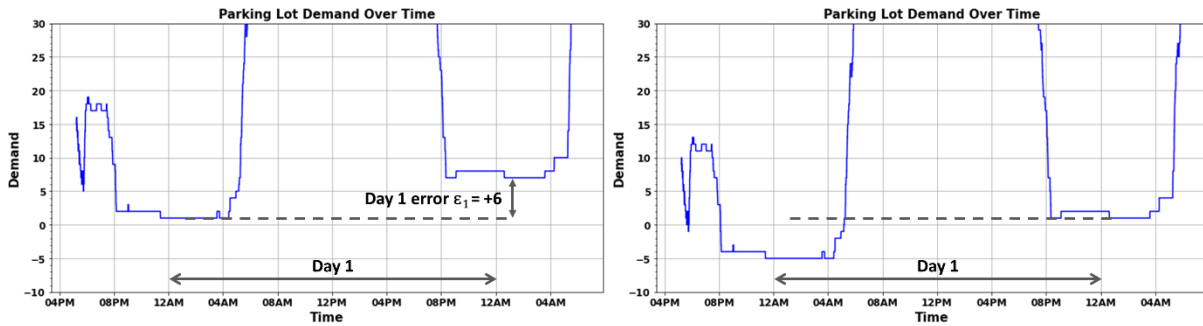


Figure 4. The graph on the left shows that six excess vehicles are predicted at the end of Day 1. Subtracting this amount from Day 1’s predicted demand eliminates the average error, as demonstrated in the graph on the right. The uniform decrease in demand on other days can be disregarded, as each error correction is applied individually to the corresponding day and is effective only during business hours.

An inspection of traffic datasets from the lots in our study revealed that they were not always empty at “dead-of-night,” as shown in Figure 5. Moreover, it is possible that one or more vehicles could have remained parked for days without being detected.

Date	Time	Channel
1/14/2025	8:15:24 PM	C to B, Lane 2
1/14/2025	8:15:53 PM	C to B, Lane 2
1/14/2025	8:16:01 PM	C to B, Lane 2
1/14/2025	8:16:12 PM	C to B, Lane 2
1/15/2025	12:11:23 AM	B to C, Lane 1
1/15/2025	3:31:25 AM	B to C, Lane 1
1/15/2025	3:46:09 AM	C to B, Lane 2

Figure 5. Although the Wellness Center closed at 8 p.m. on January 14, two vehicles entered the parking lot later at 12:11 a.m. and 3:31 a.m.

Even though determining the ground truth demand may not be possible, one can revise expected demand upward from zero as needed to improve accuracy. For example, if we choose 3:45 a.m. as the dead-of-night time for estimating demand, the sequence of timestamps in Figure 5 suggests that at least two vehicles were in the lot at that time ($\Delta \geq 2$). Creating a Python script to analyze timestamps in this manner was straightforward, enabling the automatic generation of phantom demand vectors for error correction.

Because the precise method for estimating daily error using Equation 4 does not lead to overestimations, it is generally the most effective approach for applying error correction. If a lot is not empty ($\Delta \neq 0$), the simplified method using Equation 6 always results in false negatives. In contrast, the precise method leads to fewer false negatives, and only when contributions to the ground truth are unobservable in the timestamp data.

11. Avoiding Manual Counts

Minimizing the cumulative error of a count, as described in Section 8, involves calculating the difference between the predicted and observed number of vehicles in the parking lot at the end of a count. It was previously assumed that this process required manually counting the vehicles before and after the traffic count. However, this approach can be impractical under certain conditions, such as inclement weather, crowded lots, or low visibility. In fact, manual counting can be avoided altogether, as the expected demand at the dead-of-night time can be estimated for each day by analyzing axle timestamp data, as discussed in the previous section.

Assume that the dead-of-night time (t_0) is defined as the moment the first vehicle enters the lot early in the morning following the day on which the count commenced (Day 0). If there are M days in the count and $ED(t_0 + j)$ represents the expected demand (ED) exactly j days after t_0 , the expected demand vector is:

$$(7) \quad ED(t_0:t_0 + M) = [ED(t_0), ED(t_0 + 1), ED(t_0 + 2), \dots, ED(t_0 + M)]$$

The corresponding predicted demand vector is:

$$(8) \quad D(t_0:t_0 + M) = [D(t_0), D(t_0 + 1), D(t_0 + 2), \dots, D(t_0 + M)]$$

Substituting the expected demand for the ground truth demand in Equation 4, the average daily error is given by:

$$(9) \quad \varepsilon_j = \sigma_j - \sigma_{j-1} = (D_j - ED_j) - (D_{j-1} - ED_{j-1})$$

with initial condition $\varepsilon_0 = D(t_0) - ED(t_0) = 1 - 1 = 0$.

If we sum *all* daily errors, the error terms up through Day $M - 1$ cancel out, leaving:

$$(10) \quad \sum_{j=0}^M \varepsilon(j) = D(t_0 + M) - ED(t_0 + M)$$

To fine-tune the vehicle count, the values for the D Bounce time (d) and wheelbase length range (w) parameters are selected to minimize the cumulative error in Equation 10:

$$(11) \quad \min_{d,w} |D(t_0 + M) - ED(t_0 + M)|$$

The phantom demand adjustment for each day is equal in magnitude and opposite in sign to ε_j , as defined in Equation (9).

Comparisons between the standard method (manual lot counts) and the augmented method (no manual lot counts) confirmed that utilization results were exactly the same if the timestamp data and dead-of-night times were the same. (Note that the last day of the manual count is not compared since the augmented method applies to one less day.)

These comparisons, however, are less realistic than those arising from independent optimizations, which produce different timestamp datasets that influence the predicted demand. Additionally, variations in dead-of-night times can lead to different expected demand values. “Blind” testing revealed that when the cumulative error for both methods was zero, the difference in utilization results was less than 4%, as shown in Figure 6.

	Standard Method (Manual Counting of Lots)					Augmented Method (No Manual Counting of Lots)				
	01/20/25	01/21/25	01/22/25	01/23/25	01/24/25	01/20/25	01/21/25	01/22/25	01/23/25	01/24/25
Average utilization:	29.3%	28.7%	35.8%	36.8%	36.8%	33.0%	31.9%	38.5%	39.0%	38.9%
Maximum utilization:	66.4%	61.2%	73.7%	60.8%	79.7%	70.3%	64.7%	76.3%	62.9%	81.9%
Difference:						-3.7%	-3.2%	-2.7%	-2.2%	-2.2%
						-3.9%	-3.4%	-2.6%	-2.2%	-2.2%

Figure 6. Comparison of utilization estimates when vehicles are manually counted at the beginning and end of a count versus when they are not.

12. Utilization Metrics

In this section, we present the key utilization metrics employed in the Tellico Village parking study. Utilization is defined as the ratio of predicted parking lot demand to parking lot capacity:

$$(7) \quad U(t) = \frac{D(t)}{C}$$

where $U(t)$ represents utilization at time t , $D(t)$ is the predicted lot demand, and C is the lot capacity.

Maximum utilization can serve as a useful initial indicator. If it regularly exceeds 100%, even for a short time, it may suggest a parking problem. However, in smaller parking lots, vehicles do not have much time to accumulate, so maximum utilization may not significantly exceed lot capacity.

Average utilization, measured over the course of open business hours, is another important metric. Predictably high average utilization is a positive sign for a business and can serve as a proxy for attendance. For instance, a restaurant could use historical average parking utilization data, combined

with factors like weather, menus, and promotions, to forecast guest turnout and adjust resources accordingly.

The **percentage of time that utilization exceeds a specific threshold utilization** (U_0) offers additional insights into potential parking issues. For example, if demand exceeds $U_0 = 97\%$ of a lot's capacity for 30% of a 10-hour day, this may indicate a problem with parking availability.

Peak utilization (U_{peak}) is defined as the average utilization that exceeds a specified threshold utilization (U_0):

$$(8) \quad U_{\text{peak}} = \frac{1}{\tau} \sum_{i=1}^{\tau} [U(t) > U_0]_i$$

where τ is the number of samples during which utilization exceeds U_0 . This metric is particularly useful as it can help estimate the number of additional parking spaces needed or, equivalently, the average excess demand that must be shifted to less congested times to avoid adding spaces:

$$(9) \quad \text{Average excess demand} = C(U_{\text{peak}} - 1) = D_{\text{peak}} - C$$

where C is the parking lot capacity, U_{peak} is the peak utilization, and D_{peak} is the peak demand.

If there are sampling intervals during which $U(t) > 100\%$, peak utilization is calculated using $U_0 = 100\%$ in Equation (8). For example, if a lot has 100 spaces and $U_{\text{peak}} = 120\%$, then the average excess demand of 20 vehicles suggests that the lot would need 20 additional spaces to meet peak demand.

Alternatively, redistributing the 20 vehicles to non-peak times could be a more cost-effective solution.

If there are no sampling intervals during which $U(t) > 100\%$, peak utilization is calculated using $U_0 \leq 100\%$ in Equation (8). For this study, we selected U_0 to be the ratio of current households to platted lots. This ensures that if U_{peak} is initially U_0 , the average excess demand is expected to remain below zero until buildout, at which point U_{peak} reaches 100% and excess demand becomes zero.

The **peak utilization indicator** (Ω) facilitates relative comparisons across peak utilization measurements by weighting the peak utilization (U_{peak}) by the number of samples (τ) in which utilization exceeds the threshold utilization (U_0):

$$(10) \quad \Omega = U_{\text{peak}} \cdot \tau$$

For example, if Monday's peak utilization is 120% based on $\tau = 120$ samples, and Tuesday's peak utilization is 140% based on $\tau = 80$ samples, Monday would represent the worst-case utilization because its Ω value is larger (144 versus 112).

13. Utilization Analysis: Wellness Center Parking Lot

The January 2025 utilization measurements for the Wellness Center parking lot were divided into four counts. Figures 7 and 8 display the results for the "WC2" count, conducted during the busiest week, starting on January 13. The peak utilization indicator (Ω) reached its highest level of the month on Monday, January 13.

Parking lot:	Wellness Center						
Parking capacity:	232						
Counter configuration:	L-55 layout with 2 feet spacing, Lane 1 B-to-C, Lane 2 C-to-B						
Channel configuration:	Lane closest to counter (Lane 1) is entrance lane: cars hit Channel 1 tu						
D-Bounce parameter DT (ms):	260						
Initial number of cars:	16						
Start date & time:	01/12/25 05:12 PM						
Sampling interval (seconds):	1						
Minimum wheelbase:	1						
Maximum wheelbase:	12						
Threshold utilization:	85.4%						
	01/13/25	01/14/25	01/15/25	01/16/25	01/17/25	Mean	Max
Number of intervals:	51940	51789	52198	52101	40466		
Average utilization:	45.0%	46.0%	41.2%	37.9%	46.0%	43.2%	46.0%
Maximum utilization:	93.1%	81.9%	86.2%	64.2%	83.2%	81.7%	93.1%
Peak Utilization (average utilization over 100%):	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
Number of intervals exceeding 100% utilization:	0	0	0	0	0	0	0
Percentage of intervals over 100% utilization:	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
Utilization indicator for over 100% utilization:	0	0	0	0	0	0	0
Number of intervals exceeding the threshold utilization:	1671	0	182	0	0	371	1671
Percentage of intervals over the threshold utilization:	3.2%	0.0%	0.3%	0.0%	0.0%	0.7%	3.2%
Peak Utilization (average utilization over the threshold utilization):	90.3%	0.0%	85.9%	0.0%	0.0%	35.2%	90.3%
Utilization indicator for over threshold utilization:	150867	0	15635	0	0	33300	150867
Average Excess Demand Calculations	Current	+Spaces	Buildout	+Spaces			
Peak utilization > 100%:	0.0%	0	0.0%	0			
Peak utilization > threshold utilization:	90.3%	0	105.7%	13			

Figure 7. Utilization data for the Wellness Center for the week beginning January 13.

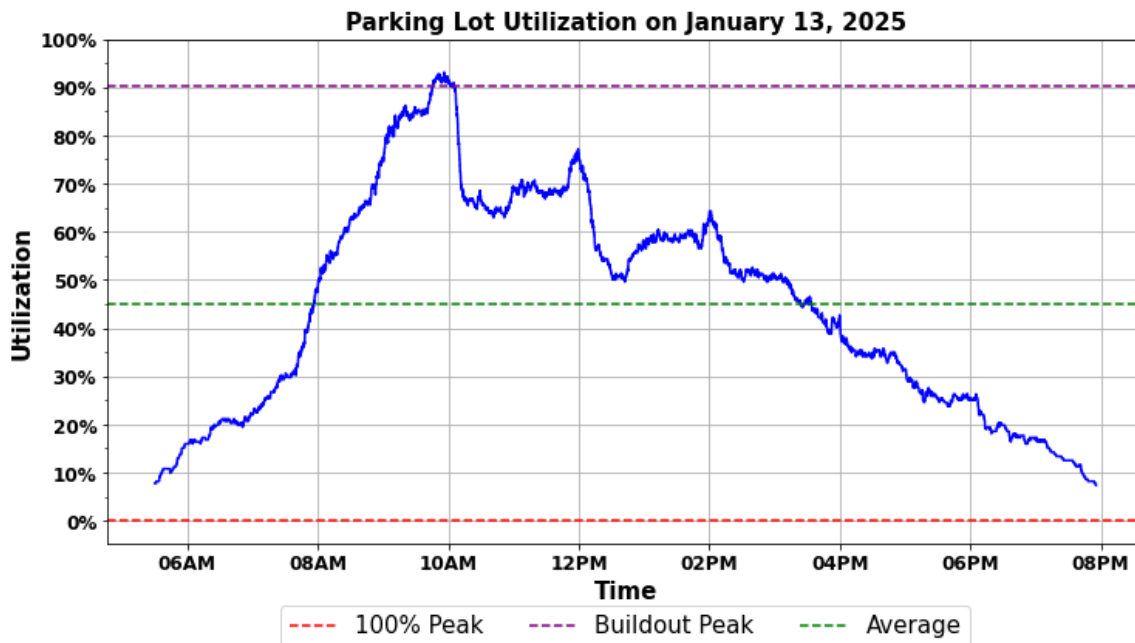


Figure 8. Utilization plot for January 13, 2025. Horizontal lines indicate average utilization exceeding $U_0=100\%$ (red) and $U_0=85.4\%$ buildout (purple), and average utilization of the day (green).

The data from all four counts (not shown) suggest that there are currently no major parking issues in January: maximum utilization never exceeded 100%, and peak utilization (U_{peak}) was always below 100%, indicating that no additional spaces are *currently* needed to meet January's parking demands.

Regarding utilization projections at buildout, U_{peak} on January 13 was 90.3%, exceeding the minimum threshold utilization, U_0 ($5,850 \text{ current households} \div 6,850 \text{ platted lots} = 85.4\%$). This suggests that by the time Tellico Village reaches full buildout, U_{peak} is expected to reach 105.7%, with an average excess demand of 13 cars in January. These vehicles may need to be redirected to less congested days or times; otherwise, the same number of additional parking spaces would be required to accommodate the anticipated increase in congestion. However, it is worth noting that the peak utilization on January 13 exceeded U_0 for only 3.2% of the hours the facility was open, equivalent to approximately 28 minutes.

14. Parking Lots

Each parking lot presented specific challenges and solutions, which are discussed below.

Wellness Center

With 232 spaces, the Wellness Center parking lot is the largest in Tellico Village. The facility experiences some of its busiest days in January, as visitors aim to get back into shape after the holidays. Measuring the lot during winter weather posed unique challenges. For instance, we had to temporarily remove the tube system in anticipation of a heavy snowstorm and subsequent snow plowing. Additionally, we discovered that mastic tape applied to the tubes is ineffective at temperatures below 30°F, as even light precipitation seeps under the strips, loosening the adhesive bond.

The Wellness Center closes at 5 p.m. on Saturdays and Sundays while it is still daylight, but inclement weather occasionally prevented weekend work. On weekdays, the facility closes after dark, making it unsafe to manually count occupied spaces at the beginning or end of a count (i.e., the observed values $\Delta(N)$ in Equation (2)). Performing these manual counts earlier in the day, while there was still light, was often difficult due to the lot being crowded.

To address these issues, we developed a method to set up and remove the tube system in under 10 minutes. First, galvanized clamps are nailed in place, and the tubes are threaded through the clamp openings. A worm gear clamp is then looped and tightened around the end of each tube, as shown in Figure 9. Since the worm gear clamp cannot pass through the galvanized clamp, the tube remains taut. Once the tubes are secured, few—if any—tape strips are required for the relatively low-speed parking measurements.



Figure 9. Use of worm gear clamps facilitated easy setup and removal of the tube system.

Toqua Bar & Grill

Toqua's parking lot experiences the most traffic from April to June, when mild weather and golf tournaments or special events attract many visitors. With 170 parking spaces, it is the only parking lot where golf carts constitute a significant portion of the vehicles—estimated to be as high as 10% of all traffic based on parking survey responses. Golfers drive their carts through the lot to access the golf course but are not permitted to park in the lot. Therefore, it is necessary to exclude golf carts from parking demand counts.

Our early experiments revealed that the JAMAR traffic counting system cannot reliably distinguish golf carts from Class 1 vehicles (e.g., motorcycles, motor scooters, mopeds, motor-powered bicycles, and three-wheel motorcycles) because their wheelbase lengths are similar. Two-seater golf carts, which account for roughly 80% of carts in Tellico Village, have wheelbases ranging from 64 to 67 inches, while 4- and 6-seater carts have wheelbases of 85 to 96 inches.

To address this challenge, we plan to filter out all vehicles with wheelbase lengths below approximately 70 inches. Since very few Class 1 vehicles enter the Toqua lot, we anticipate the false positive rate from failing to identify some carts for removal from the counts will not exceed about $10\% \times 20\% = 2\%$ of the total count. These initial estimates will be refined as additional statistics are gathered during peak times.

Chota Recreation Center

The Chota Recreation Center has the smallest parking lot of the four facilities, with only 89 spaces, and is also the most congested. When the lot reaches capacity, cars have been observed parking on the street outside the entrance. While this makes it challenging to measure the true demand for the lot, it remains useful to identify when and how often the lot exceeds its capacity.

The lot's entrance features inbound and outbound lanes separated by a raised median, necessitating the use of two counters. The counter on the inbound side will use Lane 1 (A→B) for vehicles entering the lot, while the counter on the outbound side will use Lane 2 (B→A) for vehicles exiting the lot.

A notable challenge is the presence of an inner gravel parking section that vehicles can access almost immediately after entering the main lot. This poses a potential issue because vehicles crossing the tubes at steep angles might compromise the accuracy of the count. However, we anticipate that this will not significantly impact results, as precise absolute measurements of speed, axle length, or vehicle class are less critical for our purposes than relative comparisons across all measured vehicles. Parking demand can still be accurately predicted using the methods described in Sections 7-11.

Yacht Club

The Yacht Club has 179 parking spaces and two entrances: one providing direct access to the restaurant and the other leading to the marina. Measuring parking demand requires a separate counter for each entrance.

The lot is divided into three sections connected by roadways, which complicates the task of accurately recording the number of vehicles at the beginning and end of a count. These logistical challenges necessitate careful planning to ensure accurate demand measurements across all sections of the lot.

15. Conclusion

As communities grow, proactive planning for adequate parking capacity is critical to maintaining accessibility, reducing congestion, and ensuring resident satisfaction. By assessing parking utilization well in advance of full buildout, planners can make informed decisions about expanding capacity or shifting demand to different times and days, preventing future bottlenecks before they arise.

This paper has demonstrated a cost-effective approach to obtaining highly accurate parking utilization data without requiring extensive manual observation. Using a system of road tubes connected to portable traffic counters, the methodology provided a scalable and efficient means of gathering detailed vehicle count data.

The accuracy of the system hinged on precision fine-tuning of parameters to minimize cumulative errors, followed by rigorous error correction. Parameter optimization was achieved through closed-loop interaction between the JAMAR STARnext analysis software and custom Python scripting. Beyond accuracy, practical considerations were also addressed to streamline setup and removal of the tube system, reducing labor and minimizing disruptions to daily parking operations.

By leveraging a low-cost yet sophisticated methodology, this study at Tellico Village underscores the feasibility of achieving high-fidelity parking data without straining budgets. The insights gained from such an approach empower community planners to make data-driven decisions that enhance parking availability, improve traffic flow, and optimize facility usage—ensuring that as the community grows, its infrastructure remains well-equipped to support residents and visitors alike.

Acknowledgements

I sincerely appreciate the contributions of LRPAC members Bruce Palansky, James Stutz, and Domenick Andreana, to the Tellico Village parking utilization study.

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