# MPC-699
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**Project Title**

Evaluating Different Methods for Estimating Queue Length on Access Ramps

**University**

University of Utah

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**Research Needs**

In 2005, traffic congestion resulted in 2.9 billion gallons of wasted fuel and 4.2 billion hours of time lost in traffic, translating into a total loss of $78 billion, according to FHWA (Federeal Highway Administration , n.d.).To overcome such expensive losses, transportation infrastructure need to be properly managed and maintained with the help of quantification of the current traffic intensity on transportation systems. They need the knowledge of exact traffic intensity in their transportation system in order to make necessary decisions and plan and act accordingly. Future planning can be adjusted by having an accurate estimation of traffic numbers. An accurate traffic control system also alters future resource allocations to address transportation systems' improvement.

One traffic management strategy designed to mitigate congestion on freeways is ramp metering. The promise of ramp metering systems is to alleviate traffic congestion or bottlenecks on freeways by adjusting the flow of traffic entering freeways. Ramps are often metered individually, where the ramp exit rate (entering the mainline) can be adjusted based on mainline congestion. (Federal Highway Administration, n.d.) Coordinated ramp metering is a higher-level strategy, where the exit rates across several adjacent ramps can be coordinated to reduce or eliminate mainline bottlenecks. In both individual or coordinated ramp metering systems, efficiency is gained when timely and accurate information on the ramp queue state is available. The number of vehicles queued on a ramp and the length of time vehicles spends traversing the ramp to access the mainline is important information for efficient operation. This information is also very relevant for accurately communicating traffic conditions to the public and managing user expectations regarding ramp and mainline performance. Current practice includes pavement embedded in-road detectors and over-roadway detectors.

### *In-Roadway Detectors*

There are many in-roadway sensors have been used like weigh-in-motion detectors, microloops, pneumatic road tubes, piezoelectric cables. Roadway temperature sensors. Inductive loops, and Magnetometers are the pavement embedded technologies that are frequently used till the date.

a. ***Inductive Loop***

Inductive loop detectors are pavement embedded sensor systems that uses the principle of eddy current generation. When a vehicle passes over the loop or stopped within the loop, then inductive loop sensors will be activated, which sends signals to the controller about the passage or presence of vehicle. Fig below shows the inductive loop detectors.

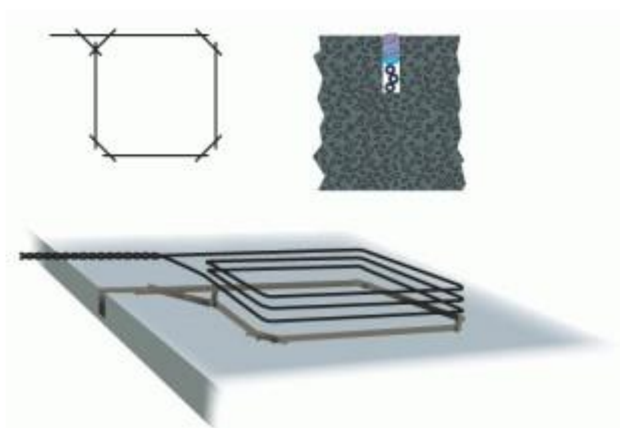


***Figure 1.*** *Inductive Loop Detectors*

Though it is reliable method, but its installation and maintenance incur huge amount of cost. Installation requires the pavement cut leading to the decrement in pavement life, frequent disruption of traffic services for maintenance, multiple detectors is needed to monitor the single locations, and detection accuracy falls when it has to detect the large variety of vehicle class.

b. ***Magnetometers***

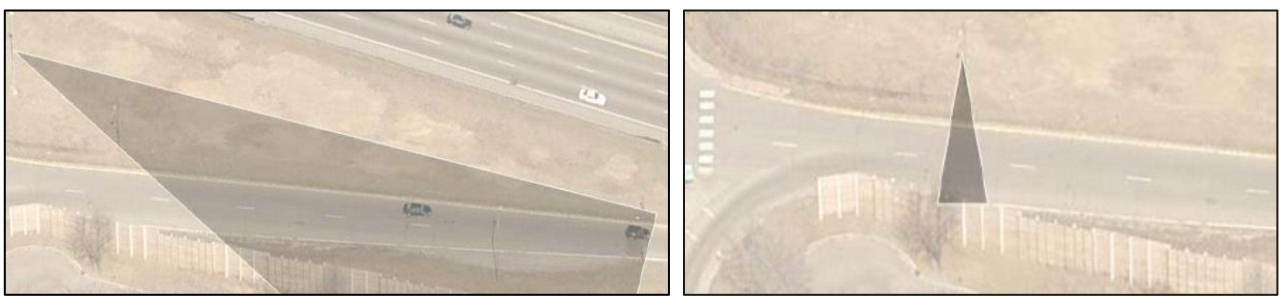
It uses the pavement embedded magnetometer sensors that communicates with the access point about detection data. It can be deployed for queue length detection and counting purpose. Count methods simply counts the entering and existing vehicle. The difference between this count is considered as queue for any given time. It needs multiple indicators and sensor-like induction loop detectors- for counting and queue length detections. For determining the queue length at least 6 sensors need to be installed in every 50 feet and evenly spaced between two lanes. For counting purpose sensors need to be configured across the lane near entrance loops. Since, this method is also in pavement embedded method, it has same drawbacks as inductive loop detectors.

### *Over-Roadway Detectors*

Video camera and radar are most used sensors-that hang on pole- as over the roadway sensors for vehicle count and queue length detection systems. Video camera's data are analyzed using image processing and computer vision tools as mentioned in this document in detail.

#### *a. Radar sensors*

This sensor used the microwave radar in forward-firing mode to detect the traffic count and queue length. Orientation of such sensor will be different based on whether the count data or the queue length estimations is required. For queue length detection it needs to be oriented as shown in below fig (a) and for counting as shown in fig (b). While performing the queue length detection sensor measures the vehicle distance from the radar and tracks the vehicles as they move through the queue and detects the slow-moving vehicles. If vehicle speed is slower than the certain threshold, it indicates that a queue has reached a certain length. In case of counting, it is placed perpendicular to the lanes and counting operation can be using the vehicle detection in region of interest. The major drawback of radar-it is unable to detect the leading vehicle from following vehicle which makes the estimation of delay -that motorist experience – very difficult.



(a) (b)

***Figure 2.*** *Arrangements of Radar Sensors (a) Queue Length Detection (b) Vehicle Counting*

Due to the extensive nature of the transportation systems, the need for an automated system to be able to calculate the traffic loads completely is inevitable. Currently, many of the highways and railroads are equipped with automated traffic control systems, such as vehicle counting. (Figure 1). Analyzing video footage from existing CCTV mounted on freeway ramps is a viable method for measuring queue lengths as well as queuing times of individual vehicles. These tasks can be automated with the use of recent computer vision and machine learning technologies. This research proposes to utilize a neural network approach (YOLO-"you only look once") (Bochkovskiy, Wang, & Liao, 2020)and DeepSORT algorithms (Wojke , Bewley, & Paulus, 2017) to estimate the number of queued vehicles, the ramp delay per vehicle as well as the overall queue state. As an illustration, Figure 2 shows two example implementations for intersections for queue length determination. Figure 3 shows the detection, tracking and calculation of delay of each individual vehicle at access ramps.

The major advantage of the video processing techniques is that it can be modified for multiple purposes like counting, queue length detection. It can easily monitor multiple lane detection and the region of interest. The purpose of task can be changed easily by feeding the input video to different set of algorithms without involving huge expenses of additional sensors, damaging the pavement, or interruption in traffic service. Same set of algorithms can be used for multiple ramps by adjusting few parameters like region of interest of analysis.

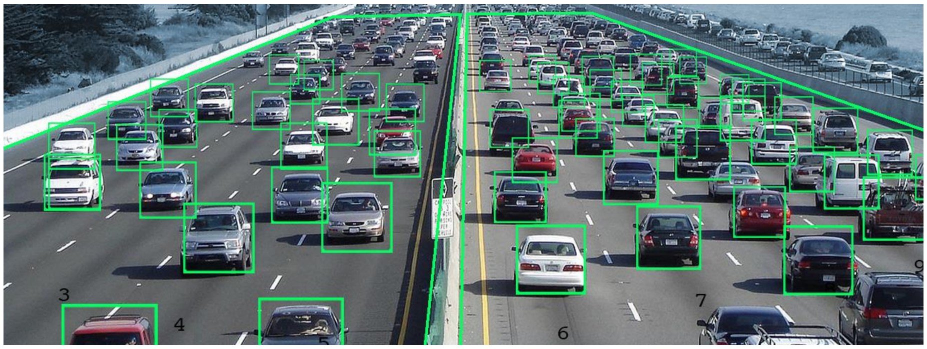


***Figure 3.*** *An Automated Vehicle Counting System*

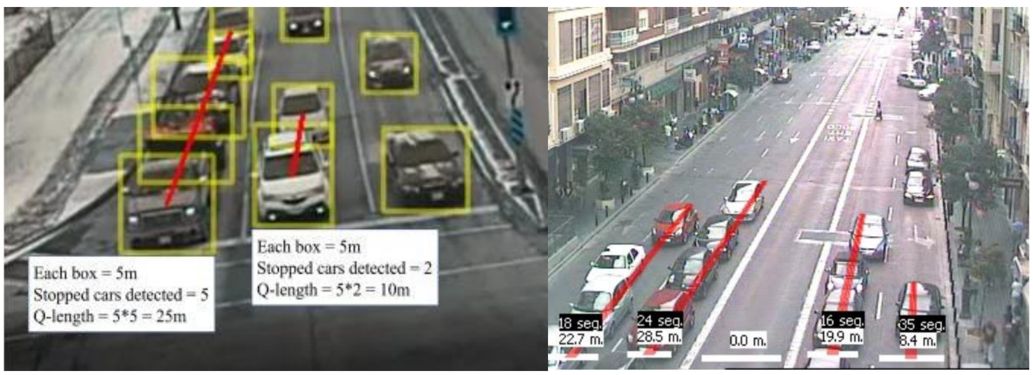



***Figure 4.*** *Queue Length Estimation Using Computer Vision at Intersections*

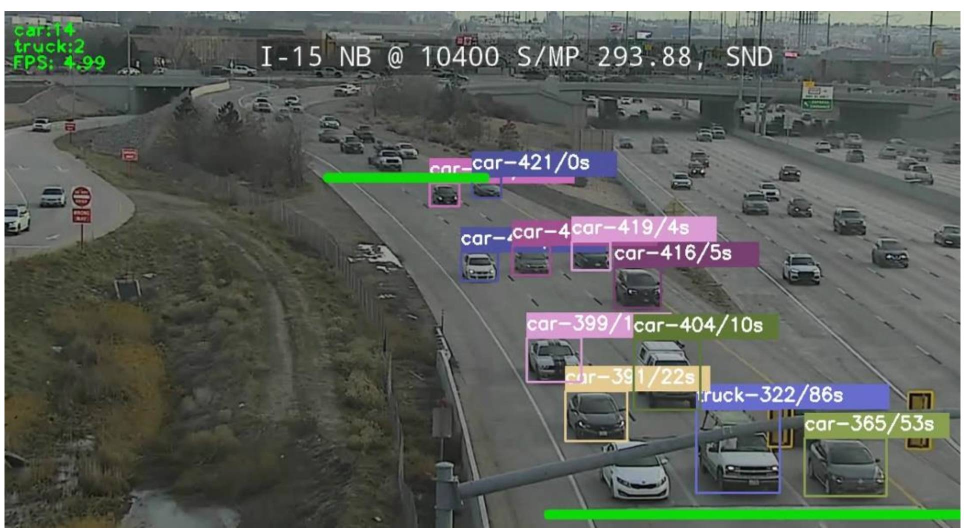



***Figure 5.*** *Vehicle Delay Calculation Using Computer Vision at Access Ramps*

Traffic control is an essential measure for strategical management of the highway traffic and smooth uninterrupted flow of highway. Getting more precise data about the entering and exiting vehicle in highway is crucial input for the traffic management team. Entering and exiting of vehicle in highway occurs through the ramp; hence the coordination of ramp with highway is very important. One of the effective coordinating measures is ramp metering. Ramp meters help breaking the platoon of entering vehicle and provides the smooth merging maneuvers. Because of this, many collisions on freeways can be reduced as it provides the smooth and efficient merging of the vehicle which are competing for the limited gaps in traffic.

In this way, traffic management teams can find out the delays experienced by the individuals at the ramps and easy determine the appropriate signal timing for each ramp by making proper coordination with other ramps nearby. This will alleviate the situation where vehicle on the busy ramps must face the longer delay. Furthermore, accurate ramp delay information will provide the basis for accurate communications to the public about ramp operations and likewise help manage public expectations regarding freeway operations. This will also allow UDOT to perform a historical examination of traffic trends along the freeway ramps as an extra advantage. UDOT, for example, will be able to identify ramps with the greatest wait times by looking at past data relevant to those ramps and maybe adjusting the ramp metering strategies at those places.

This project attempt to automate the ramp metering using the modern tools like computer vision, which is already tested for vehicle detection and counting in many highways. In this process, we can detect, track and monitor the queue length of vehicle entering at highway from the ramp to determine the appropriate signal phase. This will be done using the video analysis from the recorded video by traffic surveillance camera and computer vision tools. We plan to use deep learning-based methods for the vehicle detections and tracking the vehicle for individual vehicle delay measurement when they go through the ramps. More details about the process will be provided in the methodology sections.

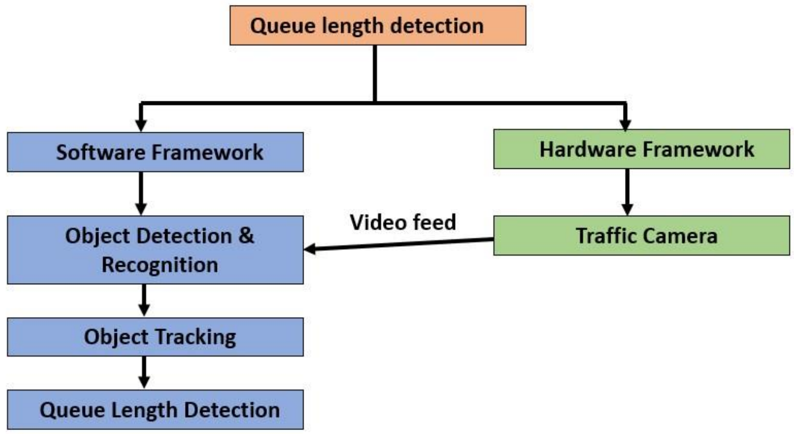
**Research Objectives**

The objectives of this research project are to:

1. Develop a computer vision-based queue length estimation system able to count the vehicle and calculate the queue length and waiting time in access ramps
2. Determine the design requirements for a full deployment of the proposed approach, such as location, height, orientation, and the necessary resolution and other technical requirements of the camera system
3. List the existing ramps (and camera technologies and configurations) that are good candidates for deploying the computer vision detection system
4. Perform a cost-benefit analysis for implementing such a system

## Research Methods

The research method consists of two major frameworks as illustrated in below flowchart.




The software framework consists of following steps:

1. Vehicle detection and Recognition
2. Vehicle Tracking

### *Vehicle Detection and Recognition*

In this work, we investigate a vision-based object detection and recognition algorithm that can be used in the design of our intelligent traffic control system. The input to the algorithm is video data obtained from a camera that is going to be mounted on highway poles. The video frame will be analyzed from frame to frame. In each respective frame, different objects are detected, and the result of detection will be used for tracking of object of different classes. Out of 80 class from Coco dataset, our algorithm will detect four major classes i.e., car, truck, bus and motorbike.

### *Vehicle Recognition*

After detecting an object in the footage recorded from our camera located at the poles, we have to recognize the class of vehicles. Our algorithm will use coco dataset to classify the detected object into Car, Truck, Bus, Motorbike. Deep Learning techniques is used for the detection and object recognition.

### *Deep Learning Techniques*

On the other hand, deep learning techniques are able to do end-to-end object recognition and classification without specifically defining features, and are typically based on convolutional neural networks (CNN).

The architecture of CNN is as follows:

**Step 1:** Convolution operation

The first building block in our plan of attack is convolution operation. In this step, we will touch on feature detectors, which basically serve as the neural network's filters.

**Step 2:** Rectified Linear Unit or ReLU (Activation) Layer

In this step, the resulted output will go through the activation function, which is usually a linear function that is designed to compute middle layers (deep layers).

**Step 3:** Pooling

It is basically reducing the size of our image in the deep layers to save us from unnecessary computational expenses.

**Step 4:** Flattening (full connection)

Inevitably, in the last layers of our architecture, we need to have all the neurons (final image pixels) to be connected in order to be able to have a better prediction on the presented object in our image. Figure 6 demonstrates the configuration of the layers.

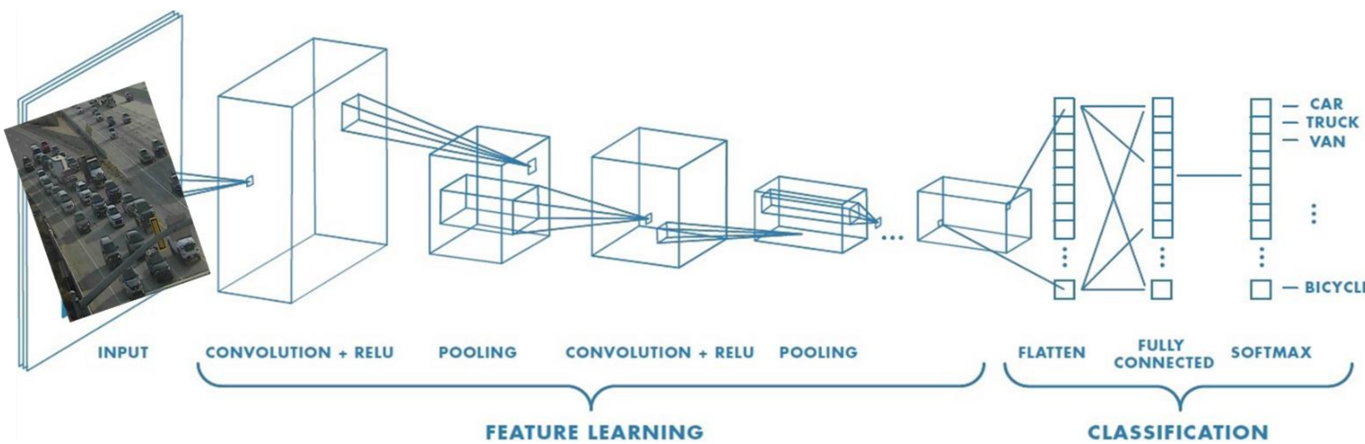



***Figure 6.*** *Layers in a Convolutional Neural Network*

In order to enhance the accuracy of the Deep Networks, we need to adjust the architecture according to the problem situation, such as adding batch normalization layers and drop out options to avoid overfitting problems. Eventually, the design of a CNN suitable for the problem is the main goal in a vision-based object recognition (e.g., aircraft recognition) task. The following are some of the object detection methods in which their back-end is a CNN.

***Table 1.*** *Prevalent Object Detection Algorithms*

| | |
|---|---|
| R-CNN | (Girshick, Donahue, Darrell, & Malik , 2014) |
| Fast R-CNN | (Girshick , Fast R-CNN, 2015)) |
| Faster R-CNN | (Ren , He, Girshick , & Jian Sun, 2016) |
| cascade R-CNN | (Cai & Vasconcelos, 2017) |
| Single Shot MultiBox Detector (SSD) | (Liu, et al., 2016)) |
| You Only Look Once (YOLO) | (Redmon , Divvala, Girshick , & Farhadi , 2016) |
| Single-Shot Refinement Neural Network for Object Detection (RefineDet) | (Zhang , Wen , Bian , Lei, & Li , 2017) |
| Retina-Net | (Lin , Goyal, Girshick , He , & Dollar, 2017) |
| Deformable convolutional networks | (Dai, et al., 2017) |

***Object Tracking***

It is also a deep learning-based approach that keep tracks of the detected objects using appearance information of the detected objects. Multiple object tracking (MOT) is done where object is detected in each frame and represented by a set of bounding box coordinates. Following different steps are followed to detect, classify and track the objects in each frame.

a. *Detection*
It uses the CNN based model detection framework. This stage extracts features and proposed regions for the second stage which then classifies the object in purposed region to identify the object into different classes.

b. *Estimation model*
This model propagates the target's identity into the next frame and make an approximation of inter-frame displacements of each object with a linear constant velocity model. When a detection is associated to the target, the target state is updated using the Kalman filter using velocity component.

c. *Data Association*
To assign the detection to an existing target, each target bounding box new location is predicted and IOU (intersection over union) distance is used between each new detection and predicted target of bounding box from earlier frame. Hungarian algorithm optimizes this problem with better accuracy. IOU threshold is significant factor for handling short term occlusion of tracked objects.

d. *Creation and deletion of track identities*
Certain track identities were given to recognized object in each frame. When a new object-with different features- is seen in a frame new tracking identities is assigned for an object. After object stops appearing in the frames for certain number of frames, its corresponding identities is automatically deleted. This number of frames depend upon the age criterion of track id i.e., means to hold that tracking id up to how many number of other consecutive frames though object is not seen in the frames.

There are various tracking algorithms with deep learning-based architecture.

***Table 2.*** *Prevalent Object Tracking Algorithms*

| | |
|---|---|
| Simple Online and RealTime Tracking (SORT) | (Bewley , Ge, Ott, Ramos, & Upcroft, 2016) |
| DeepSORT | (Wojke , Bewley, & Paulus, 2017) |
| FairMOT | (Chu, Wang , You, Ling , & Liu, 2021), |
| TransMOT | (Chu, Wang , You, Ling , & Liu, 2021), |
| ByteTrack | (Zhang , et al., 2022) |

### *Hardware Framework*

Hardware framework comprises of the camera that are already installed in highway for traffic surveillance. For current study, video obtained from four of those cameras will be taken as data for the research. Few videos will be used for the model development process and others will be used for test and validation purposes. Additionally, optimal height, orientation, location, and resolution of camera will be suggested for future installation of traffic-cams.


The result obtained from this method with be used for comparative analysis with other prevalent available methods that are being implemented at present condition despite having few drawbacks and error.

### Expected Outcomes

The expected outcomes for this project will include the following items:

1. Determining the queue length and waiting time at access ramps.
2. Optimal Location, height, orientation, and resolution of cameras for any future deployment will be determined.
3. Identification of the exiting ramps with the potential for implementing a computer vision-based system.

### Relevance to Strategic Goals

**Primary strategic goal:** Economic Competitiveness

The proposed queue length and waiting time calculation system will assist the decision makers to better plan for the traffic flow management at highway access ramps, better assign resources, avoid high volumes of traffic by preventing bottlenecks, thus reducing the mainline congestion and overall delay. Additionally, it increases the freeway traffic throughput. This ultimately leads to saving fuel prices that would be otherwise spent in congestion. Also, pavement doesn’t need to be disturbed while installing and maintaining the camera, it reduces the maintenance cost of pavement and increase pavement life. Camera is already placed at intersection and ramps for other traffic incident management, video from the same resource can be utilized thus saving an extra cost for the installation and maintenance of other redundant technology.

**Secondary strategic goal:** Safety

An automated detecting and tracking vehicle at ramps before entering the highway will eventually result in better management of the traffic and avoids potential mishaps, accidents, clashes, etc. by effective coordination between ramps and highways. This coordinated system will break the platoon from access ramp vying for the space in mainline thus reducing the collision between vehicle approaching from access ramp with vehicle from mainline.

### Educational Benefits

The PIs of this project are currently teaching two graduate level class called "CVEEN 6790: Advanced Computer Aided Construction" and "CVEEN 6530: Quantitative Methods for Transportation Operations". It is expected that the developed algorithms, methods, and case studies in this project will be directly converted into new course materials for these courses. In addition, a number of selected undergraduate and graduate students will be participating in different steps of this project including data collection, processing, and validating the obtained results.

### Technology Transfer

The technology transfer process for this project will take place through two major channels: 1) publishing (presenting) research results in scholarly journals (conference proceedings); and 2) direct interactions with UDOT personnel as the potential end users for the results of this study.

### Work Plan

1. Project start date: August 1, 2022
2. Conduct literature review: August - September 2022
3. Prepare list of queue length estimation approaches: August - September 2022
4. Collect data from available resources: September 2022 - March 2023
5. Develop computer vision model: October 2022 - June 2023
6. Perform data analysis and evaluate results: November 2022 - August 2023
7. Draft report complete: August - September 2023
8. Report revision: September - October 2023

### Project Cost

| | |
|---|---|
| Total Project Costs: | $108,000 |
| MPC Funds Requested: | $ 48,000 |
| Matching Funds: | $ 60,000 |
| Source of Matching Funds: | Utah Department of Transportation |

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