I-95 CC – Volume & Turning Movement Project
Steering Committee Meeting #8
August 16, 2018

Agenda:

	Topic	Speaker
1	Welcome & Project Status Update	Denise Markow, I-95 Corridor Coalition Stan Young, NREL
2	Traffic Volume Estimation using GPS Traces: Florida and New Hampshire Update	Zachary Vander Laan, UMD CATT
3	Insights from VTM Error Analysis	Stan Young, NREL
4	Future Work - Next Steps & Wrap Up	Stan Young, NREL Denise Markow, I-95 Corridor Coalition

Meeting Notes:

- ***Project Tasks Status Update – Stan Young, NREL***

    o Reviewed the project goals, objectives, and status
    o Reviewed why we need more and better volume data
    o Explained the concept of ubiquitous traffic volumes
    o Discussed the proposed solution – an estimator that ingests probe data and other information and outputs traffic volume
    o Reviewed the current outlook on accuracy measures and the general accuracy question, "How good is good enough?"

- ***Traffic Volume Estimation using GPS Traces: Florida and New Hampshire Update – Zachary Vander Laan on behalf of Kaveh Sadabadi, UMD CATT***

    o Overview
        ▪ Explained this is a continuation of previous work on the Florida dataset and expansion to New Hampshire data
        ▪ Reviewed objectives – building a model based on probe data, archived data, and continuous count data from select locations
        ▪ Reviewed the model training process and how it is applied to state probe count data

    o Florida dataset – Q4 2016
        ▪ INRIX GPS probe data (75M strips, 3.4B points) – 2.1% median probe penetration
        ▪ HERE probe speeds
        ▪ Roadway characteristics (number of lanes, speed limits, facility types)
        ▪ Weather data

- TTI hourly volume estimates
- High-quality ground truth count data from FDOT

o The Volume Estimation Model
  - Dense Artificial Neural Network (ANN)
  - Trained model using data from 172 of 173 count stations and tested against the excluded count station – then repeated 172 more times with different new count stations
  - Compared computed volume estimates against ground truth and generate metrics

o FL Model Results
  - Overall Metrics – 0.83 R^2, 25% MAPE, 7% EMFR
  - Model performs well on several different functional classes, but with some degradation in performance at low volumes
  - Showed statewide maps with model estimates on volumes
  - The model first estimated hourly volumes and the team rolled those up into AADT and AAWDT. Error on the AADT and AAWDT were low – so this is a viable way to estimate AADT.
  - The team also tested estimates on freight volumes – performance on highest functional road class is similar to overall model. Lower functional classes were not performing as well. There isn't a lot of probe data on those lower functional class roadways which hurts model accuracy.
  - The team is currently developing flags for unusual behavior – whether the input data is questionable or model outputs are questionable. These will be based on whether the input data or estimates are within some number of standard deviations from the mean.

o New Hampshire Dataset – Q3 2017
  - INRIX GPS probe data (7M trips, 595M waypoints) – 2.3% median probe penetration
  - Probe speeds – RITIS and various vendors
  - Roadway characteristics (number of lanes, speed limits, facility types)
  - Weather data
  - TTI hourly volume estimates (optional)

o NH Model Results
  - Overall Metrics – 0.84 R^2, 27% MAPE, 7% EMFR
  - Used Transfer Learning – leverages the model from Florida (or another state with a large data set) to help train a better model in New Hampshire (much smaller dataset)
  - The team tested several ways of model training:
    - Purely Florida model
    - Purely NH model
    - Florida model fine-tuned with NH data
    - A model trained on both NH and Florida data.
  - The model trained with both data sets performed the best

- - The team also trained a model on the entirety of the Florida data and added segments of NH data in two-week increments. With just two weeks of NH data the model actually performs really well for predicting NH volumes.
    - This shows a large benefit for smaller states because the team can use models trained on large datasets to predict volumes in states with smaller states where it's hard to acquire a lot of data.
  - Questions:
    - Q: Keith Miller (NJTPA) - I realize that this issue isn't specifically germane to the work that you've been doing, but given that the "penetration rate" is about 2%, have you investigated whether there are any important biases in the sample? For example, more trucks, or more high-income travelers? This may impact how the model performs...
    - *A: Zach Vander Laan (UMD CATT) – there is a pie chart that shows distribution of probe data and for the particular data set we're using, it does tend to have more trucks. That said, the models are capable of adjusting for that kind of input data – the target output of the model is the actual vehicle count from the continuous count stations. That may be a different distribution of vehicles, but the model can learn the relationship between trucks in input data and the true volume data as an output.*
    - Q: Daivamani Sivasailam (MWCOG) - Looks promising but a few questions. The weather in Florida and New Hampshire will be different in winter. Another factor which affects volume is terrain - flat in Florida versus rolling in New Hampshire. Does this mean that these two factors do not affect the performance of the model?
    - *A: Zach Vander Laan (UMD CATT) – NH dataset was Q3 while FL was Q4 – so we did get some end-of-the year weather. There are certainly some differences between the two. That's why the FL model directly ported over to NH data has some problems, but the models are good at picking up different kinds of input data and associating those factors with the correct volume outputs.*
    - *A: Stan Young (NREL) – This phase of VTM has been proof of concept, and our next step is prototype. We'll be getting to full years of data and seeing if these factors have any deeper effect on model output.*
    - *A: Denise Markow (I-95 CC) – One of the reasons we chose Q3 NH data (core summer months) was that it would more closely resemble a Q4 FL data set.*

- ***Insights from VTM Error Analysis – Stan Young, NREL***
  - Symmetric MAPE (SMAPE)
    - Low volumes provide issues when using MAPE
    - SMAPE adds the ground truth and estimate and divides by two
    - Stops low-volume error from dominating MAPE measures
    - This measure works well for off-freeway performance calculations
  - Training bounds and data filtering
    - The team noticed large errors at high volumes – was this due to the lack of appropriate training data?
    - Error decreased continuously up to 5000 veh/h, then increased dramatically as volumes increase. As absolute volume increases, sampling

theory would indicate error would continue to decrease – the team's guess was there was not enough training data, which was confirmed.

- Looking at residual vs. probe count plots – the team found data outside of training bounds which provides error.
- The team also found many cases of areas with zero reported probes. The ground truth data showed vehicles on the roadway but the probe counts were near-zero. In the future, the team will be flagging issues with probe counts like this.

o Performance during unusual events
- The team took a look at how well the system performs when unusual events happen
- The team took each location and hour of the day, then separated observed volume data from each of those into a 0-5% of occurrences range, 5-50% range, 50-95% range, and 95-100% range and calculated error measures from the model in each of those bins.
- Model performed best in the 5-95% range, but the 0-5% and 95-100% still performed well (these are extremely unusual circumstances).
- Divided the observed volume data from +/- 1, +/- 2, and +/- 3 standard deviation ranges. Each standard deviation from the mean represented a class of incidents which would decrease volume (1 to 2 standard deviations would be an incident or normal weather, 2 to 3 standard deviations would be a fatal accident, special event, or snow storm, and 3 or more standard deviations would be an extremely rare event like a blizzard, eclipse, or hurricane).
- The model performed very well in most of these standard deviation bins except for more than 3 standard deviations from the mean, but this bin represents less than .1% of all observed volume data.

o Questions and Comments:
- C: Steven Jessberger (FHWA) – noted that there are issues with large volumes due to the way lane changes and other types of irregular vehicles may be detected. FHWA also studied different events (SB, festivals, extreme weather) and expected errors and FHWA is happy to provide that document.
- Q: James Li (MWCOG) - It seems that normal distribution is used for all time periods. I was wondering the assumption behind. Can you shed some light on it?
- A: *Stan Young (NREL) – we debate this internally often but at this point we're sticking with gaussian distribution. We're doing this now to keep our assumptions uniform.*

- *Wrap up – Stan Young, NREL*
  o There is a small addition of research funding but we anticipate this phase closeout at the end of 2018.
  o The team thinks a proof of concept has been established, but to get to prototype phase we'll be doing continued work.
    - NREL & UMD – metric/error analysis/confidence

- ▪ NREL – finding additional coalition states
- ▪ UMD – truck volumes and vehicle types analysis
  - o VPP has been going on for a decade now and we're getting ready for VPP 3.0 (we anticipate including everything from VPP 2.0 but also including volume estimate work. We're collaborating with data providers now.).
  - o OD data (trace data) is on the horizon
  - o We're discussing this project with several states as a method of getting 'from the lab to the streets'.
  - o USDOT through FHWA is recruiting states for a PFS (TPF-5(384)) and the official memo has been issued. It will look for new sources of volume data for HPMS. More details can be found here: https://www.pooledfund.org/Details/Study/636
    - ▪ The objective of this pooled fund project is to develop and deploy methods and approaches to obtain vehicle volume and classification data with passively collected data.

- • ***Closing Remarks & Discussion – Denise Markow,* I-95 Corridor Coalition**
  - ▪ Denise thanked all members for their participation and asked for input about next steps relative to the project.
  - ▪ Final Questions/Discussion
    - o Keith Miller (NJTPA) - I understand that you can correct for the oversampling of trucks, but I think it would be important to check for other sampling biases that may not be in the count database, for example, are income classes represented accurately? What about short vs. long trips?
    - o *A: Stan Young (NREL) - The data comes without attributes attached but we're looking at ways we can get that kind of data from vendors. We can follow-up offline.*
    - o Denise Markow: how does the model learn how to adapt to different truck volumes in input vs. output?
    - o *A: Zach Vander Laan (UMD CATT) – the model sits between the input and the output. In a linear regression, it's easy to understand how each variable affects the output. In machine learning, it's difficult to describe how this process works because the ANN is a black box. We provide inputs – we don't just provide counts, but we also provide weight class for each probe as we receive it from the vendor. The model tries to take a look at the probe counts and weight class and provide the best estimate. That's why we look at the error analysis based on ground truth to determine how the model is performing.*
    - o *A: Stan Young (NREL) – If you look at the error analysis we did, we didn't know probe count could flatline, but the model actually figured that out without our knowledge.*

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