



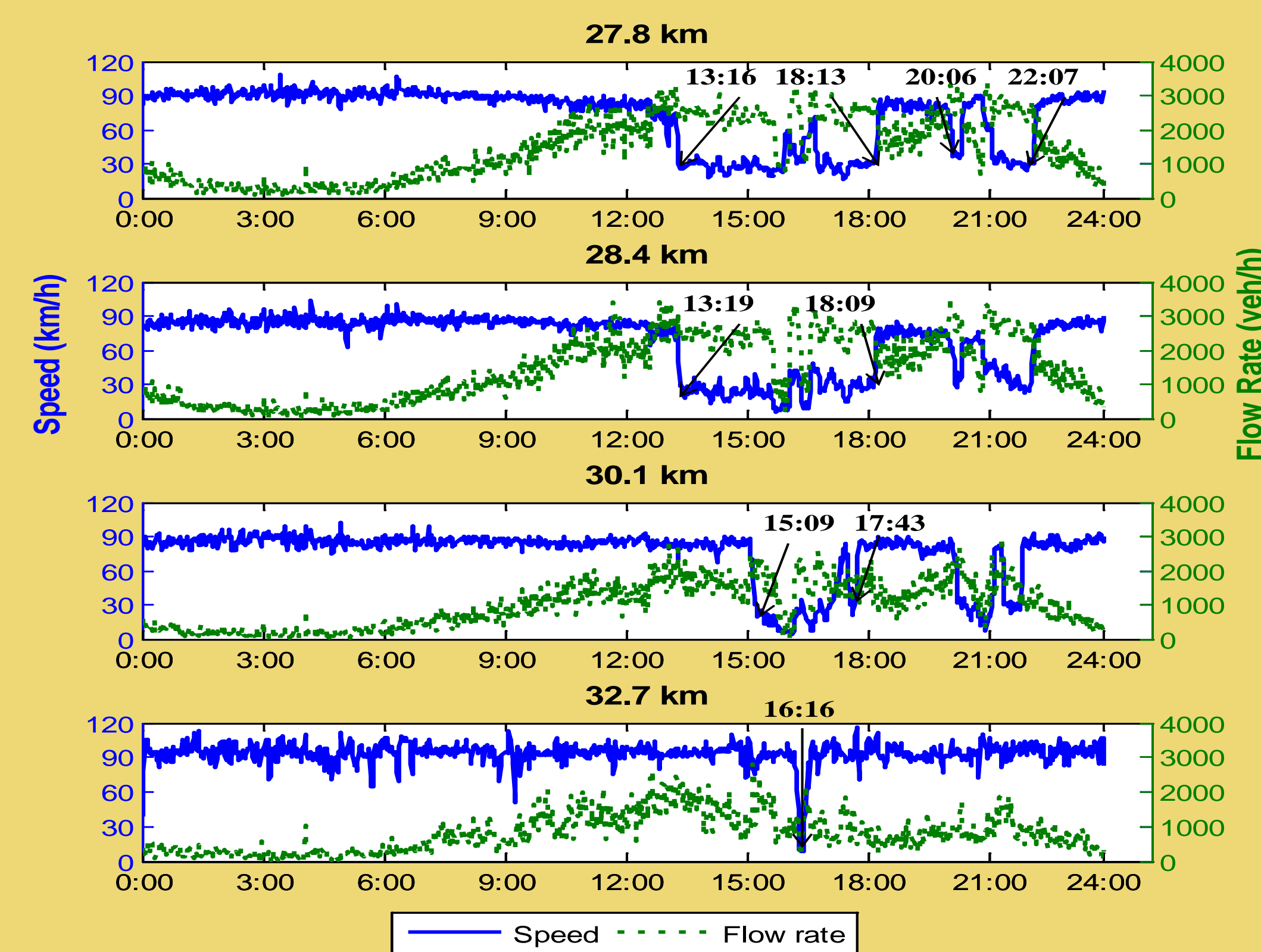
# A Dynamic Monitoring System for Predicting the Long Highway-tunnel Impact on Traffic Breakdown: A Case Study

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## Abstract

- Due to the apparent capacity difference between Hsuehshan tunnel and its connected roadway segments, identifying the optimal activation time for available control strategies has emerged as a critical issue.
- This study presents an exploratory system that integrates an existing macroscopic model with a dynamic monitoring function that serves as the basis to guide the selection of a new set of parameters when the traffic condition within the tunnel is evolving into the unstable state.
- Using one year of field data, our experimental results show the promising properties of the system which can serve as the basis for guiding the activation of the control strategies in a timely manner.

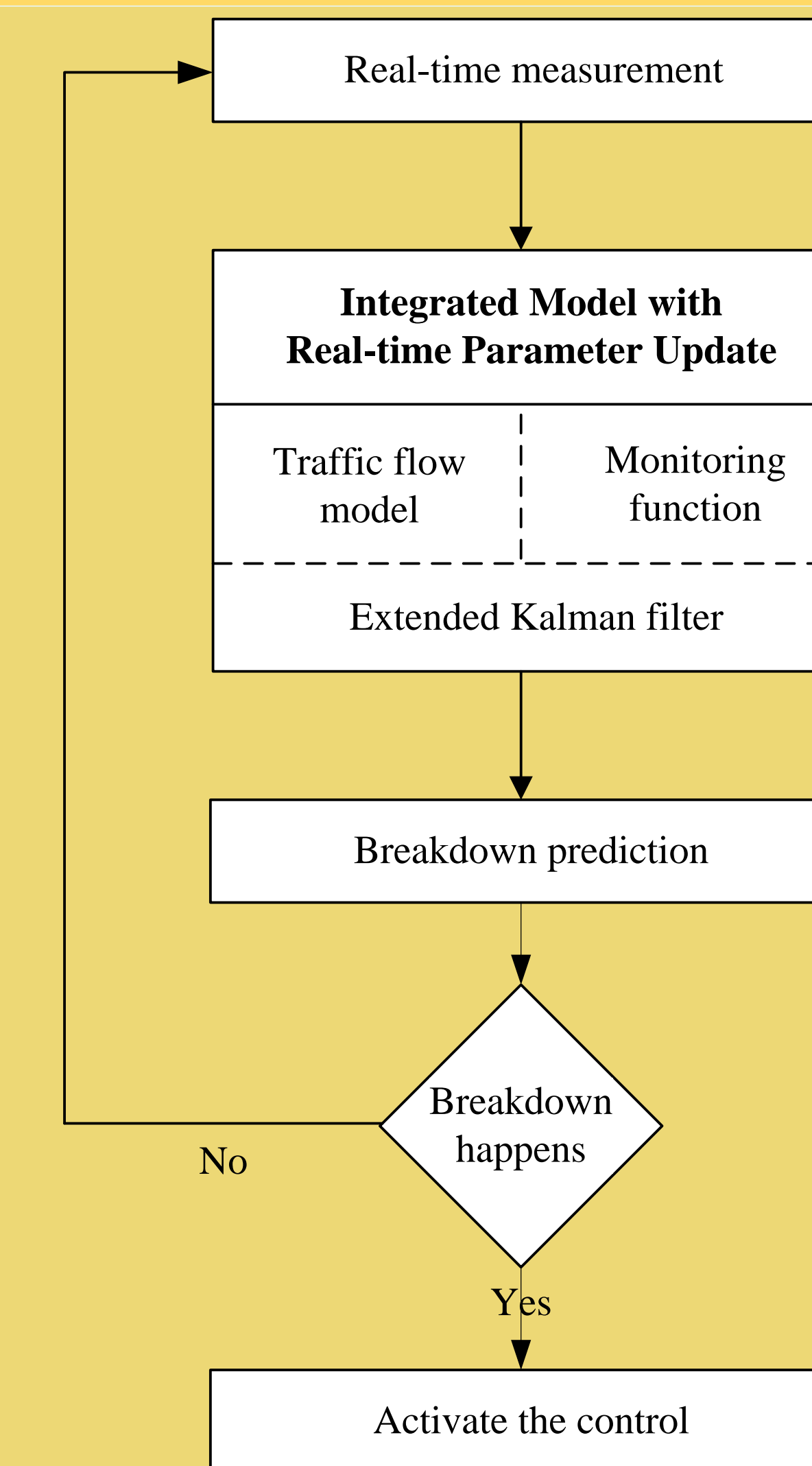
## Empirical Data Analysis



The data demonstrates the need to activate control strategies in a timely manner so that the freeway traffic conditions do not reach its breakdown state and take an excessively long time to recover.

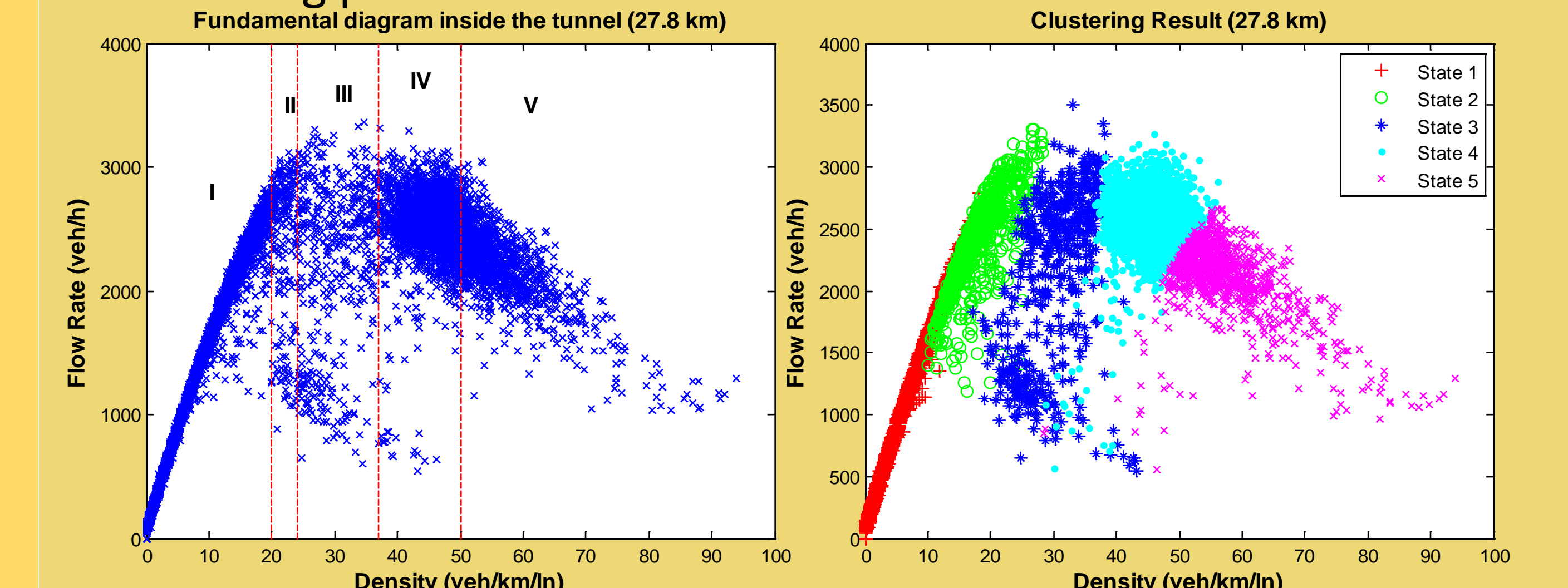
## Methodology

- The first component is a well-calibrated second order METANET model.
- The monitoring function for the segments inside the tunnel is used to detect and classify the resulting traffic state in order to improve the overall modeling accuracy.
- The identified traffic state will then serve as the basis for the traffic model to select a new set of parameters.
- The extended Kalman Filter (EKF) is implemented to update all key parameters in real time.



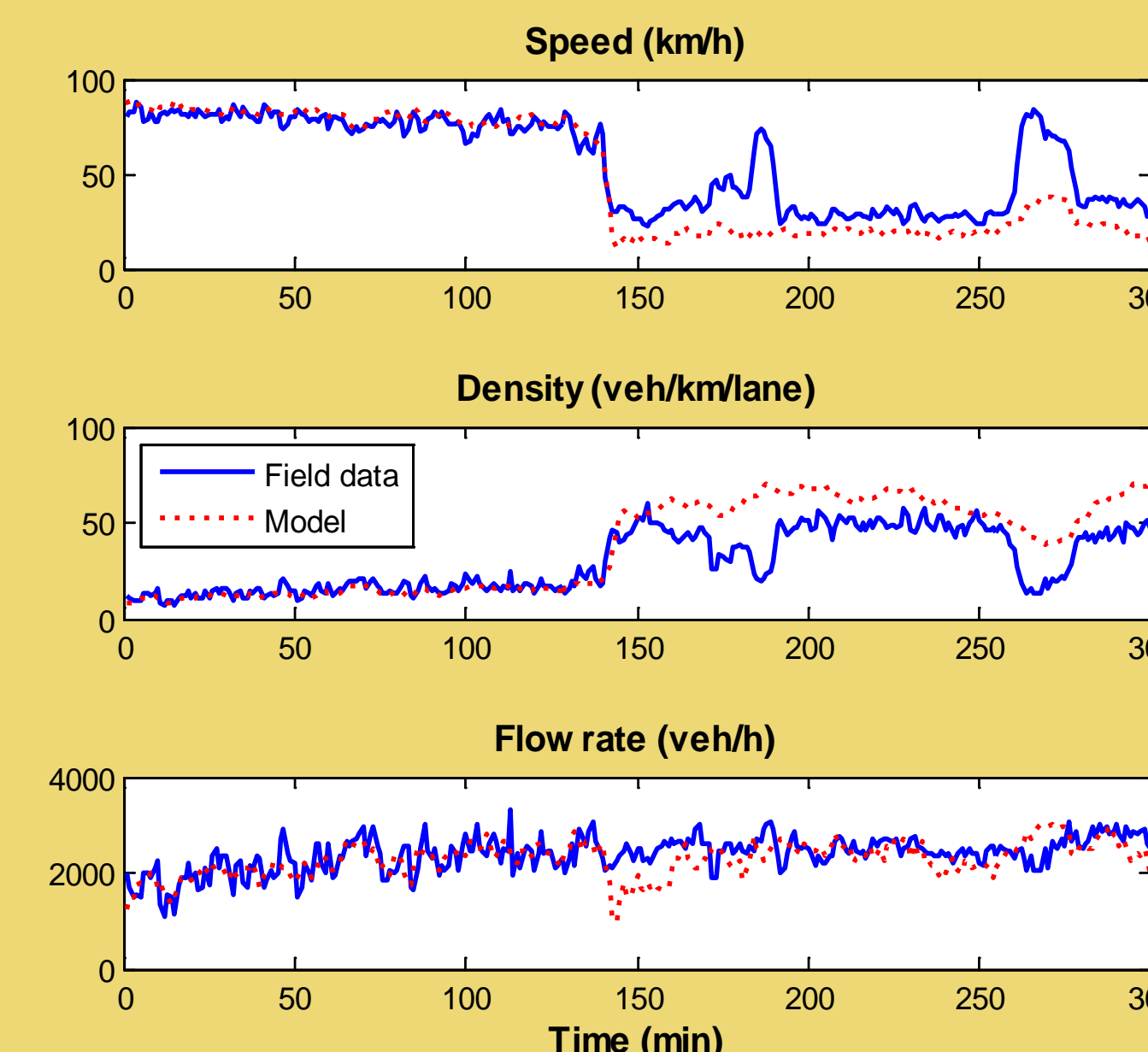
## Integrated Prediction Model

- The traffic flow characteristics within the tunnel are quite different from the non-tunnel upstream segments when the traffic state exceeds some critical level.
- A monitoring function is proposed to guide the traffic flow model on when to change its parameter set so as to best perform its prediction function.
- The advantage of the K-means method lies in its capability to concurrently consider flow rate, speed, and density in the clustering process.

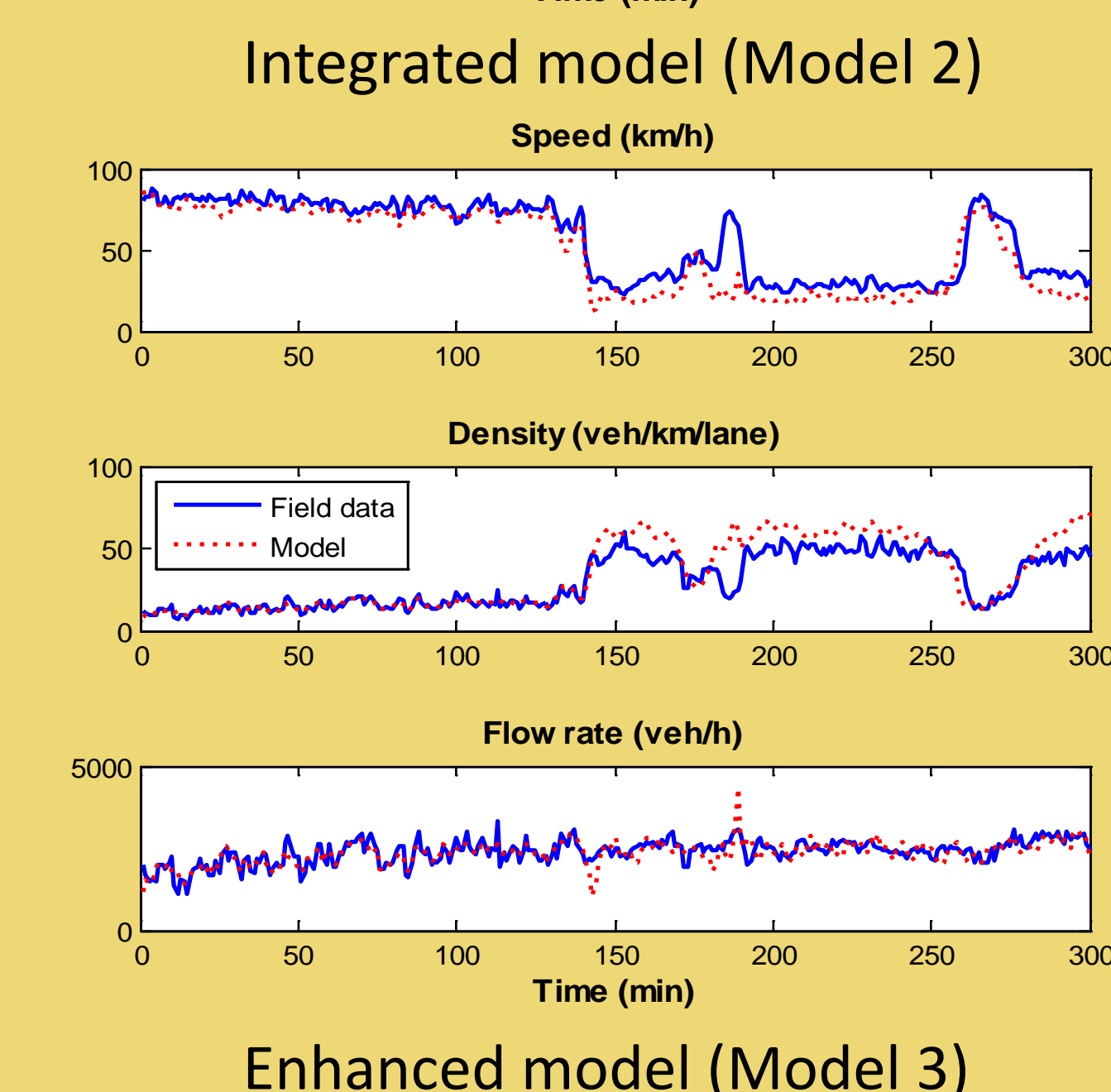
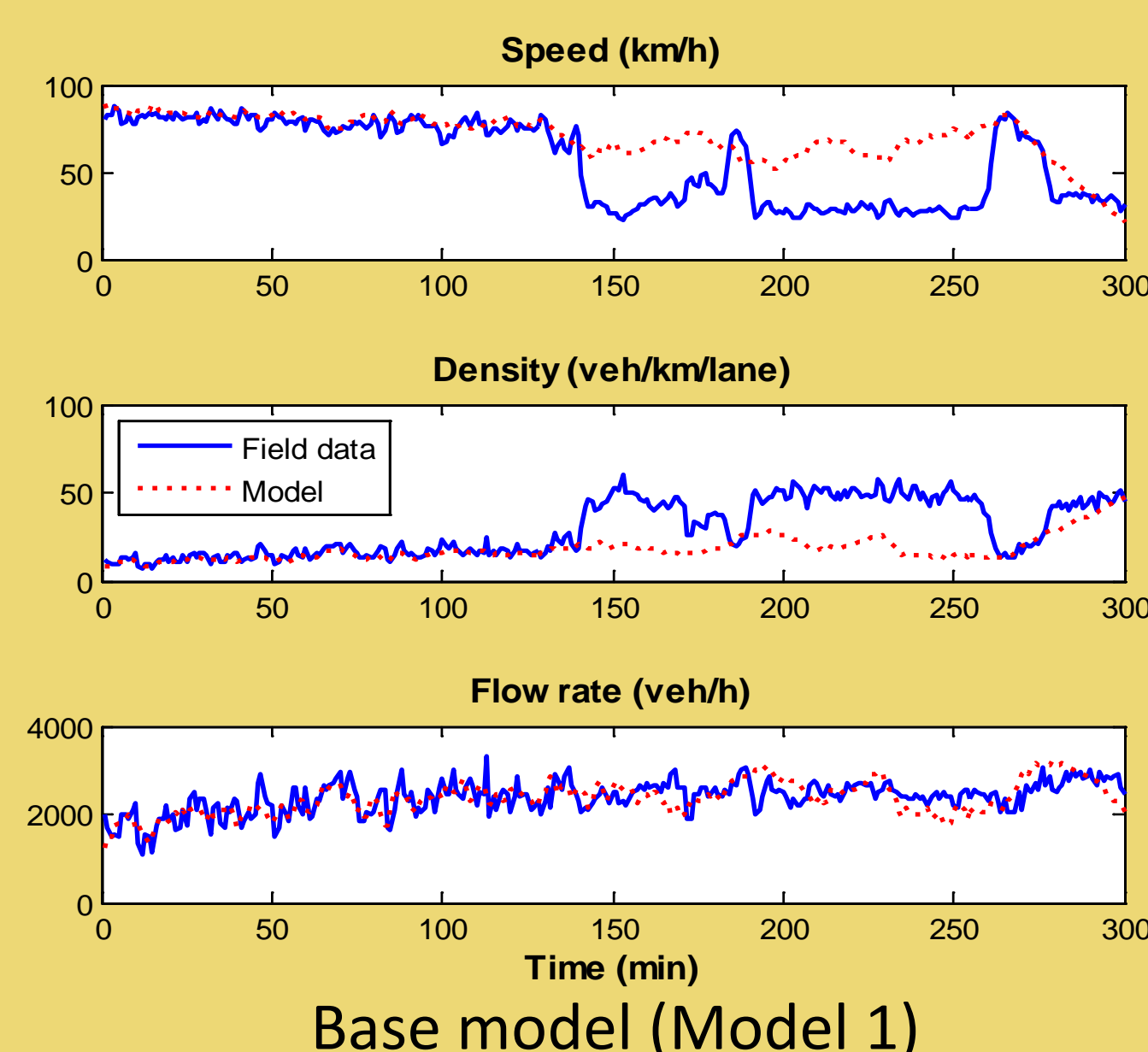


## Model Comparison

Flow rate	Day	1	2	3	4	5	6	7	8	
	Model 1	11%	13%	20%	11%	10%	11%	13%	8%	
	Model 2	12%	14%	23%	13%	11%	12%	16%	11%	
	Model 3	8%	11%	17%	9%	10%	10%	14%	7%	
	Day	9	10	11	12	13	14	15	16	Average
	Model 1	14%	18%	13%	11%	9%	15%	12%	11%	13%
	Model 2	19%	24%	14%	12%	9%	15%	13%	13%	14%
	Model 3	14%	13%	10%	8%	8%	10%	10%	10%	10%
Speed	Day	1	2	3	4	5	6	7	8	
	Model 1	45%	35%	40%	54%	53%	62%	52%	89%	
	Model 2	12%	12%	16%	14%	13%	21%	25%	24%	
	Model 3	10%	10%	14%	10%	12%	18%	22%	18%	
	Day	9	10	11	12	13	14	15	16	Average
	Model 1	88%	102%	46%	40%	62%	54%	49%	40%	57%
	Model 2	31%	31%	16%	21%	14%	18%	24%	17%	19%
	Model 3	22%	32%	14%	20%	12%	15%	18%	14%	16%



- The models to be compared are the base model, the integrated prediction model, and the enhanced model with both monitoring function and real-time parameter updates.
- The speeds from both enhanced models drop at the same time interval as the field data.

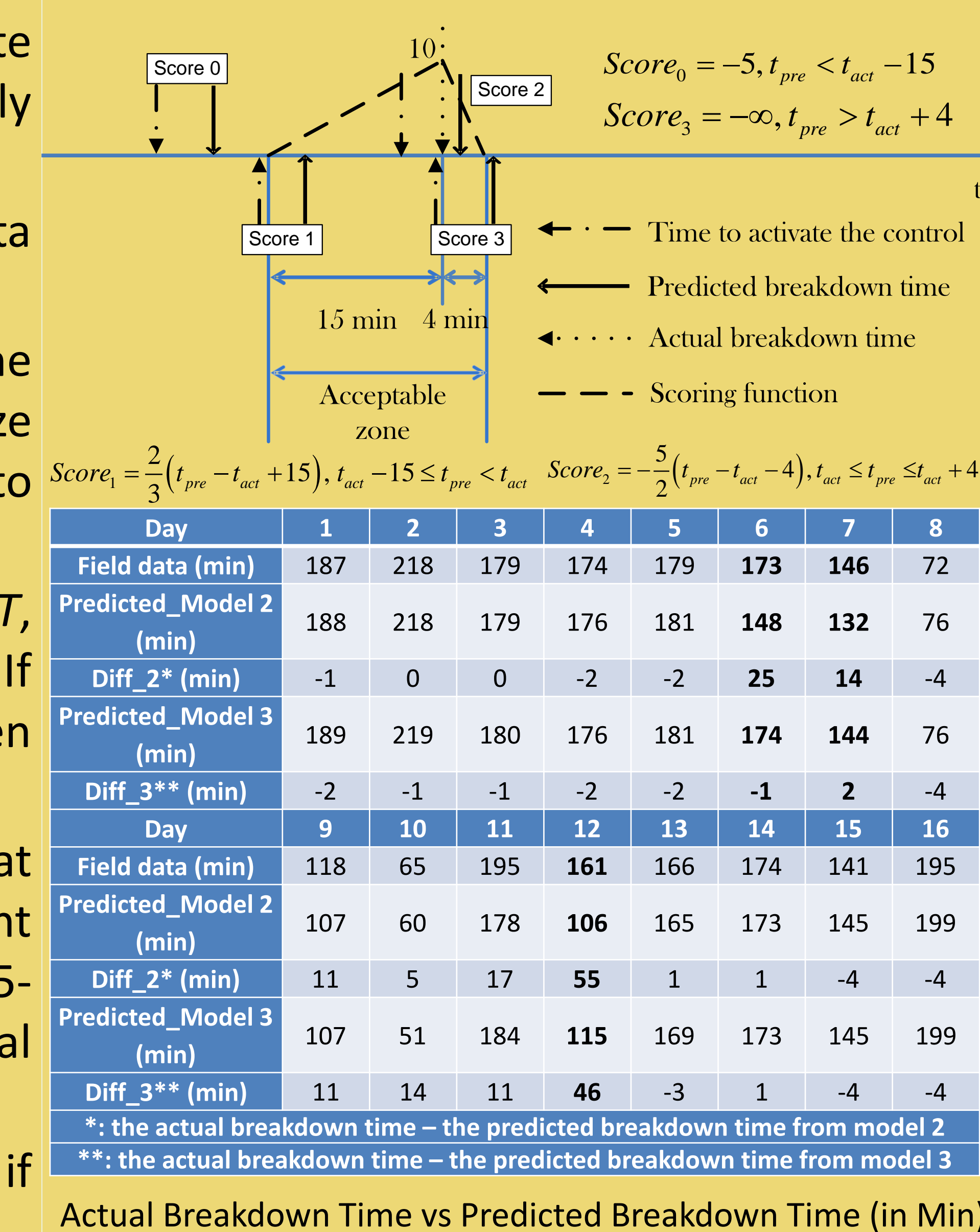


## Breakdown Prediction

### Prediction Algorithm

- Step 1. **Prediction**: At time  $T$ , predict the traffic state from time  $T+1$  to  $T+10$ , based on previously proposed models.
- Step 2. **Classification**: Cluster each predicted data point into one of the five traffic states.
- Step 3. **Initialization of Flag value**: At time  $T$ , the state, predicted for 4-min ahead, is used to initialize the *Flag* variable, which is given a larger value to account for the congested condition.
- Step 4. **Calculation of the Flag value**: At time  $T$ , there are a total of 6 predicted states for time  $T+5$ . If any of these predictions indicates congestion, then *Flag* value will be increased by one.
- Step 5. **Decision**: The control will be activated if at least half of the predictions for one time point suggest the evolution to the breakdown, or the 5-min ahead prediction from the current time interval indicates the presence of severe congestion.
- Step 6. Return to Step 1 when clock turns to  $T+1$ , if no control is activated.

### Evaluation of breakdown prediction algorithms



## Conclusions

- A breakdown prediction algorithm for the freeway tunnel segment has been proposed on the basis of traffic flow models.
- Tunnel traffic condition was first classified into one of five states using centroid-based clustering methods.
- A monitoring function on the basis of obtained traffic states was then developed to decide the appropriate choice of model parameters.
- Upon implementing the monitoring functions, capacity drop phenomenon can be modelled by the second-order macroscopic traffic flow models.
- The proposed model can be used to forecast the traffic breakdown. Moreover, the extended Kalman filter was adopted in the enhanced model to improve the modeling precision.
- Volume prediction algorithms for upstream arrival need to be taken into account.
- Other future extensions include the development of the integrated control algorithms to mitigate the tunnel bottleneck congestion.