Automated Classification of Different Congestion Types

Barbara Karl[1], Lisa Kessler[1], Klaus Bogenberger[1]

Abstract— **Congestion on freeways can be caused by different sources and therefore needs different treatment for traffic control and optimization. Advanced traffic analysis is required to improve traffic efficiency. This paper presents a definition of four congestion types, (a) Jam Wave, (b) Stop and Go, (c) Wide Jam, and (d) Mega Jam. Through virtually driving trajectories passing a spatio-temporal area, the type of a congestion can be automatically determined. Each congestion can be categorized depending on certain parameters. A sensitivity analysis and a parameter optimization are conducted.**

I. MOTIVATION

Road traffic constantly increases and therefore also congestion on freeways. Transportation institutions and authorities aim at giving proper statistics with analyses of the prevailing traffic situations and congested regimes. Often, every institution has got its own interpretation of traffic jam. Some authors define congestion if the speed falls below a certain threshold, others describe a congested area if the measured speed values suffice certain spatial and/or temporal conditions. The published statistics widely vary since there is no unique congestion definition. Additionally, the definitions even from the same institution change from one year to another [1].

The authors of [2] mention various reasons of congestion like construction sites, accidents, intense traffic, or human errors. While at construction sites and accidents the traffic is slowed down because of complications on the road, intense traffic can be effected by strong rush-hour or holiday traffic or due to low capacity caused by the infrastructure (e.g. lane reductions, junctions, slopes). Human errors might be sudden deceleration or unnecessary lane changes [3].

Since a congestion can have many different causes, it behaves individually in its spatial and temporal extensions. Several different congestion types may occur depending on the speed reduction cause. In order to optimize traffic control, each type of congestion needs a different treatment. This paper aims at giving a congestion definition and at identifying different congestion types according to their characteristics to receive a more accurate ground truth.

This paper is organized as follows. Section II gives an overview of existing congestion definitions and congestion type classifications. In section III, an automated classification of congestion types using virtual trajectories is explained. The proposed method is applied to a data set of a German autobahn in section IV and also a sensitivity analysis of the parameter set is executed. Section V summarizes the paper and gives an outlook on future work.

[1]The authors are with the Institute of Intelligent Transportation Systems, Bundeswehr University Munich, Neubiberg, Germany barbara.karl@unibw.de

II. STATE OF THE ART

In the literature, there exist several approaches how to bound congested from free-flow traffic, studies with a fixed or a variable velocity or with a travel time threshold. The public radio station of Bavaria sets the threshold to 40 km/h, traffic jams in Switzerland are defined with a threshold of 10 km/h [4]. INRIX [5], [1] define congestion if the speed in one of their segment-based links falls below a certain percentage of the average free-flow velocity at normal traffic. The online information portal of Bavaria *BayernInfo* [6] detects traffic jams below 32 % of the free-flow velocity (which is at most 130 km/h). TomTom [7] define congestion as certain amount of additional travel time during peak hours compared to one hour of driving during free-flow conditions.

Besides the congestion definition, also several approaches of congestion classification have been topics of research. Kerner et al. defined three phases of traffic whereof two represent congested phases. These phases were extended by Helbing et al. to five different kinds of congested traffic states. In a cooperation between BMW and TRANSVER, four congestion types were mentioned. The following subsections explain the congestion classification evolution.

A. Kerner's Approach

A basic and well-known traffic state classification is the three-phase traffic theory developed by Kerner and Rehborn [8]. The evaluation is based on the analysis of extensive datasets of congestion patterns on German and international freeways [9], [10]. This theory distinguishes three different phases of traffic: free-flow, synchronized flow and wide moving jam.

The wide moving jam phase is a congested stretch that propagates upstream with a constant mean velocity as one coherent structure through all other traffic states or bottlenecks. In synchronized flow, the downstream front is usually fixed to a certain location as for example bottlenecks [11], [9], [12].

B. Helbing's Approach

In [13], Helbing et al. derive conditions for congested traffic states, starting from the instability diagram of a traffic flow model. They analyze the occurrence, appearance, spreading in space and time, and the related increase in travel time. The terminology of traffic phases is discussed and an empirical evidence of the existence of a phase diagram of traffic states is given. In contrast to other presented phase diagrams, it is shown that *widening synchronized patterns* are possible if the maximum flow is located inside of a metastable density regime. Apart from different discussions and investigations, it is pointed out that combinations of on- and off-ramps create different patterns than a single isolated on-ramp. The elementary patterns from [13] are:

- Moving localized cluster
- Pinned localized cluster
- Oscillating congested traffic
- Homogeneous congested traffic
- Widening synchronized pattern
- Stop-and-go waves

Localized clusters have a length which remains stable and covers a short motorway section. Pinned localized clusters are congestions fixed to certain locations, whereas moving localized clusters propagate upstream with a characteristic speed. The two congested states *oscillating congested traffic* and *homogeneous congested traffic* stretch over longer motorway sections. Frequently oscillating speeds in the congested area are characteristic for the *oscillating congested traffic*. In contrast, the *homogenous congested traffic* has a constant low speed in the congested area. The *stop-and-go waves* are several speed break-downs in a row [13].

C. BMW/Transver Approach

In a report from BMW/Transver [14], traffic jams are analyzed based on GPS tracks of individual vehicles and stationary detectors. Different characteristics have been investigated and typical congestion formations have been identified. The driven velocity and the time of each vehicle with this driven velocity are two significant values for an identification. These values are applied for the classification of a traffic jam in general, and also for the distinction if it is the same or a new traffic jam. In a first step, the velocity threshold defines a congested spatio-temporal area. If the velocity is above the defined threshold value for a certain time period, the next velocity break-down is counted as a start of a new congestion. The following parameters were identified:

- Congestion duration
- Average congestion velocity
- Standard deviation of the average congestion velocity
- Duration of the phase with very low velocity

After identifying the congestion, it could be classified. In [14], four definitions are mentioned.

- Jam wave (single speed break-down)
- Stop-and-go waves
- Wide jam
- Mega jam

The single congestion wave is a thin stripe implying a temporarily low velocity. The *stop-and-go wave* are several narrow stripes representing congestion waves separated by free-flow sections. The *wide jam* is a broad area with predominant congestion velocity. An extensive area with the domination of speed values under the critical velocity is the *mega jam*. It represents a wide-spread traffic breakdown.

III. Methodology

In the following, an approach to automatically categorize a traffic situation is presented. Using virtual trajectories, the speed trends of single vehicles crossing the congested area are analyzed and applied for distinctions. First, a traffic speed reconstruction is needed (spatio-temporal speed distribution). This can be received either from stationary sensors like loop detectors, from mobile sensors like floating cars, or from travel time measurements. Stationary sensor data need to be smoothed, e.g. using the *adaptive smoothing method* [15], [16]. Floating-car data can be spatio-temporally reconstructed using the *phase-based smoothing method* introduced by Rempe et al. [17] where the three phases defined by Kerner (see subsection II-A) are recognized. Travel times for example from Bluetooth measurements can be reconstructed by the algorithm proposed by Kessler et al. [18].

In all cases, the result is a spatio-temporally interpolated traffic speed reconstruction as shown in Fig. 1. Let T be a set of time intervals $t_1, \ldots, t_n$ and let X be a set of location intervals $x_1, \ldots, x_m$. Sets $\{t_i\}_{i=1,\ldots,n}$ and $\{x_j\}_{j=1,\ldots,m}$ divide the spatiotemporal area $T \times X$ into a grid with cells $t_i \times x_j$. Each cell is assigned a speed value $v(t_i, x_j) =: v_{ij}$.

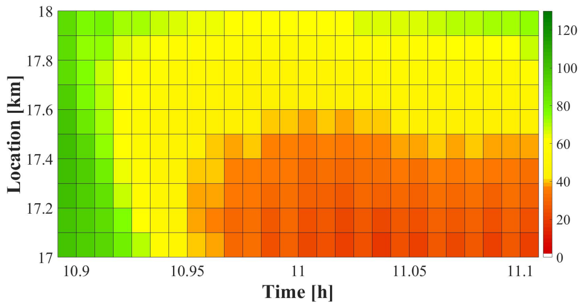

Fig. 1. Discretized speed matrix with temporal cell length of 30 s and spatial cell length of 100 m

The method proposed here is based on the congestion type definition [14] presented in subsection II-C, where the evaluation method is extended by virtual trajectories. This methodology is a transparent approach due to its simple parameter definition. A virtual trajectory is a path through the speed matrix which can be started at the corner of any cell (t_i, x_j) of the spatio-temporal grid. The speed of the trajectory corresponds to the speed of the cell v_{ij} following the derivation $\partial x/\partial t$ per cell. Whenever the trajectory reaches the bounds of the cell, it continues to the neighbored cell with the prevailing speed there. An exemplary trajectory is shown in Fig. 2.

At the end, this trajectory crossed a set of cells with their respective speeds. The result is a speed progress over time, illustrated in Fig. 3. By analyzing its speed trend, one single trajectory can identify a congestion and check for fulfillment of the type classification.

The velocity threshold defining a congested regime is the critical velocity v_{crit}. To differentiate one congestion to another, the duration of coherent prevailing speed above v_{crit} after a break-down must be at least t_{break} (Fig. 4).

Each trajectory can determine which kind of congestion it has passed. Fig. 5 shows the congestion type classification from a starting point in time t_0. Applied to the speed trend

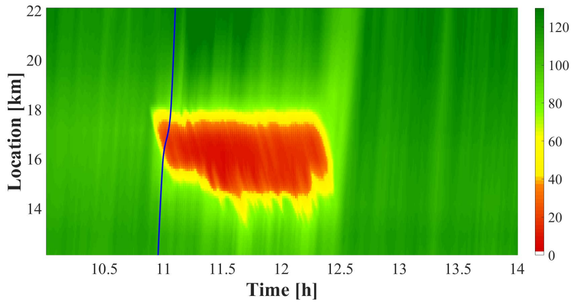

Fig. 2. Trajectory (blue) in a spatiotemporally discretized grid starting around 11 a.m. at km 12

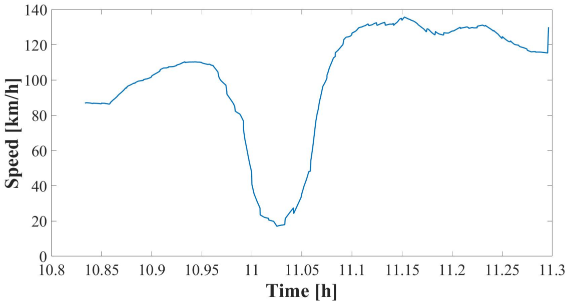

Fig. 3. Speed progress of the trajectory shown in Fig. 2

(Fig. 3), the trajectory is classified as type *Wide Jam* if the parameters are set to $v_{crit} = 40$ km/h, $\Delta t_{JamWave} = 3$ min, $\Delta t_{MegaJam} = 30$ min.

The automation comes into play if several trajectories cross a congested region starting at different times. Each trajectory gets assigned one type of congestion. If all trajectories passing the congestion result in the same type, the congestion is assigned this kind. In case that various trajectories return different congestion types due to the temporal shifts of the start of each trajectory and the variable progress of the formation of a jam, the congestion type is set to the most frequently assigned classification. Fig. 6 shows the entire congestion from Fig. 2 with 17 trajectories, starting with a temporal distance of 5 min. Only trajectories that detected a congestion are visualized. The result shows that the first 16 drawn trajectories were classified as *Wide Jam* whereas the last trajectory touches the congestion pattern just shortly wherefore it was classified as *Jam Wave*.

IV. Application and Sensitivity Analysis

Considering Figs. 4 and 5, the classification of the four different congestion types depends on several parameters. To get a proper definition of the different congestion types, a variation of these parameters and a sensitivity analysis are executed in the following. The analysis is only applied to single congestion clusters, not to several jam patterns on the same spatio-temporal traffic reconstruction.

A. Data Set

The methodology presented was applied to data derived from autobahn A9 near Munich, Germany. The stretch covers 47.7 km in northbound (NB) direction and 31.4 km in southbound (SB) direction. Stationary road sensors measured local speeds between April and June 2015. The speed is a flow-weighted mean over all car and truck lanes per minute [19]. The data have been interpolated applying the *Adaptive Smoothing Method* (ASM) [15], [16] to derive smoothed speed values for the space between the detector positions (33 detectors in NB, 27 detectors in SB) [19]. The ASM parameters used are as shown in Tab. I.

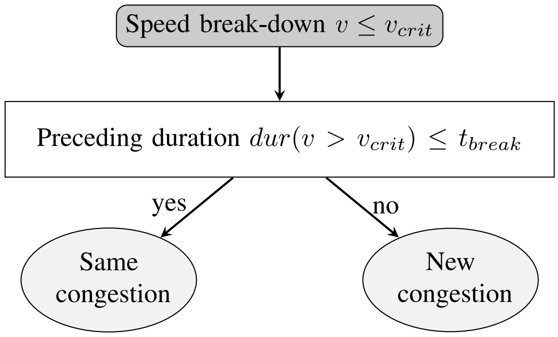

Fig. 4. Distinction of same or new congestion (based on [14])

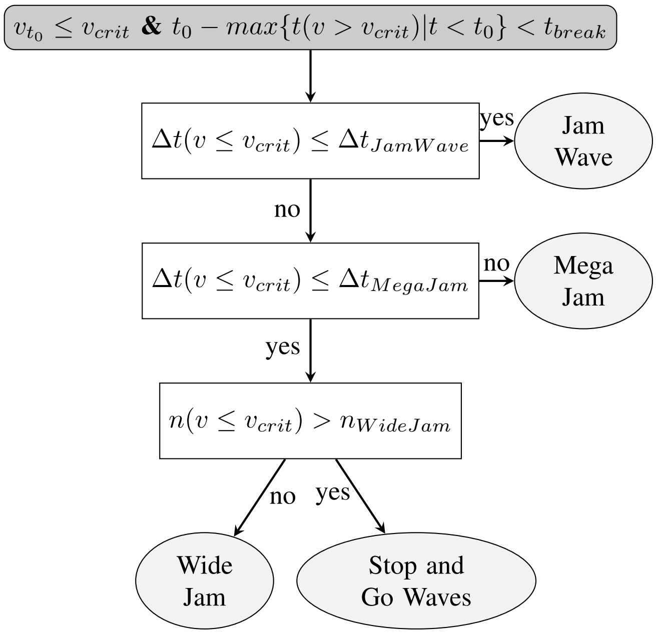

Fig. 5. Schematic representation of congestion classification (based on [14])

B. Parameter Definition with Base Value

The initial parameters are inspired by [14]. The main parameter is the critical velocity v_{crit} determining the occurrence of a congestion (Fig. 5). The time interval to decide if a congestion is a *Jam Wave* or a *Wide/Mega Jam* is the maximal duration of a Jam Wave $t_{JamWave}$. The time between two velocity drops is called t_{break}, it classifies the congestion type *Stop and Go* with several Jam Waves. The minimal duration of the Mega Jam $t_{MegaJam}$ distinguishes between *Wide Jam* and *Mega Jam*. To determine a *Stop and Go* congestion type, the number of speed drops during one

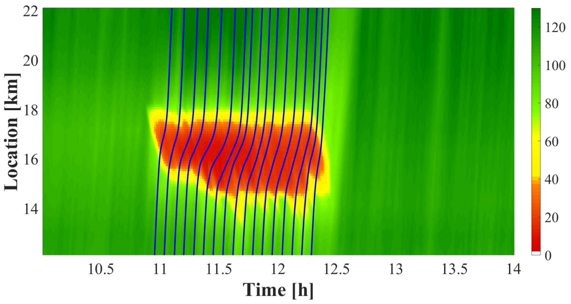

Fig. 6. Trajectories passing the congestion of typ *Wide Jam*

TABLE I
ASM PARAMETERS USED FOR SMOOTHING THE DETECTOR DATA [19]

Parameter	Value
Spatial grid distance	100 m
Temporal grid distance	30 s
Speed in congestion	-18 km/h
Free-flow speed	80 km/h
Crossover from free to congested traffic	70 km/h
Width of the transition region	10 km/h

congestion is necessary, the parameter is called $n_{StopandGo}$. Furthermore, it is parametrized how many trajectories are created. The base value n_{traj} is set to twelve trajectories per hour, hence the temporal time shift amounts to 5 min. The base line of the parameter set can be found in Tab. II.

TABLE II
PARAMETER DEFINITION WITH BASE VALUES

Parameter	Base Value
Velocity threshold v_{crit}	40 km/h
Maximal duration jam wave $t_{JamWave}$	3 min
Minimal break between speed drops t_{break}	4 min
Minimal duration mega jam $t_{MegaJam}$	30 min
Minimal number of speed drops $n_{StopandGo}$	3
Number of trajectories per hour n_{traj}	12

C. *Parameter Variation*

The six parameters introduced in IV-B are modified. Each parameter varies in both directions as it is illustrated in Tab. III. First, each parameter is modified separately and the other parameters are kept constant. In the second step, several parameters are changed simultaneously. Additionally, one calculation with all parameters set to their minimum and one with all parameters set to their maximum is executed. For each congestion type, one or two data sets were chosen. Findings of this investigation are taken for an additional analysis on a larger amount of data.

D. *Sensitivity Analysis*

In the following, one or two congested areas for each congestion type are exemplarily investigated while exactly one parameter is varied. The traffic situation with the congestion type *Jam Wave* is shown in Fig. 7. The variation of

TABLE III
VARIATION OF THE PARAMETERS

Parameter	From	Step Width	To
v_{crit}	35 km/h	5 km/h	55 km/h
$t_{JamWave}$	1.5 min	0.5 min	4.5 min
t_{break}	2 min	0.5 min	6 min
$t_{MegaJam}$	20 min	5 min	60 min
$n_{StopandGo}$	1	1	6
n_{traj}	1	1	60

all parameters does not take any effect on the classification of this traffic formation. Additionally, a similar traffic situation was considered and the behavior was the same. Just the variation of the parameter $t_{JamWave}$ led to a change in the classification of single trajectories. If this parameter is larger than the base value, more *Jam Waves* and less *Wide Jams* are classified. Nevertheless, the amount of trajectories classified as *Jam Wave* prevail in the two exploring scenarios.

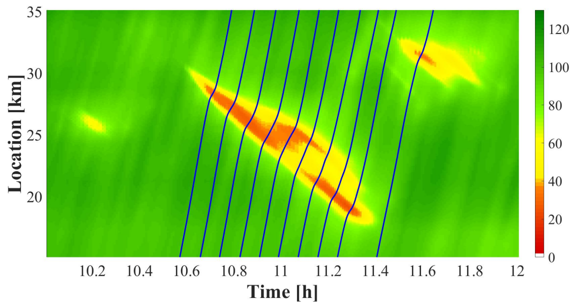

Fig. 7. Trajectories crossing the congestion type *Jam Wave*

The classification of a *Wide Jam* is depicted in Fig. 8 (additional to the *Wide Jam* in Fig. 6). This congestion is passed by 12 trajectories and 9 of them are of the type *Wide Jam*, while the others are classified as *Jam Wave*. The latter ones are trajectories at the beginning and the end of the congestion pattern since they recognize the traffic jam shorter than the other trajectories in the middle of the pattern. This congestion type is rather robust towards parameter variation; by increasing $t_{JamWave}$, most trajectories change from *Wide Jam* to *Jam Wave*. By reducing n_{traj}, the type of this congestion is recognized more unreliably.

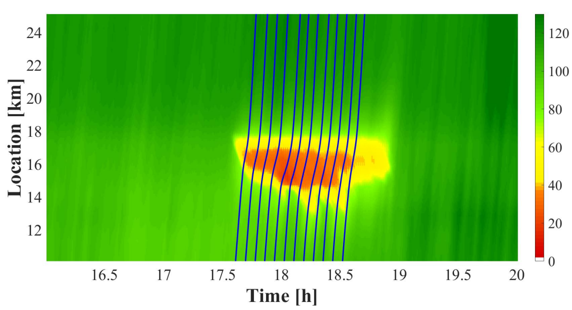

Fig. 8. Trajectories crossing the congestion type *Wide Jam*

In all investigated congestion patterns, more trajectories of type *Stop and Go* are classified if v_{crit} is increased or if $n_{StopandGo}$ is reduced to 2. In this case, most trajectories in the congestion shown in Fig. 9 are classified as type *Stop and Go*. But this congestion pattern matches also many trajectories classified as a *Mega Jam*.

The congestion type *Mega Jam* is difficult to examine because of the low data availability with mega jams. The automated classification yields to roughly the same amount of trajectories of both types. The overall type depends on the parameters. Between 12 and 16 h, the traffic jam behaves like a *Mega Jam*, and between 16 and 20 h, the formation resembles more like *Stop and Go* waves (Fig. 9).

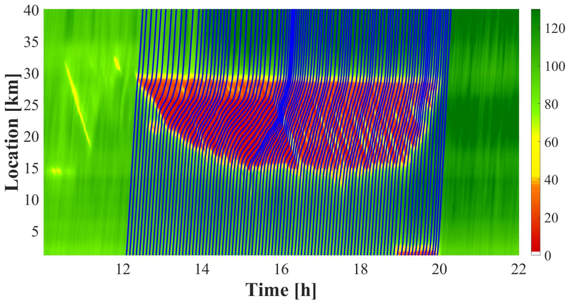

Fig. 9. Trajectories crossing the congestion type *Mega Jam*/*Stop and Go*

The variation of t_{break} effects trajectories classified as *Jam Wave* or *Wide Jam*. This could be observed for example in the congestion depicted in Fig. 10. Several neighbored speed drops occur, they could be categorized either as *Jam Waves* or as one *Wide Jam* and the pattern later on as one separated *Jam Wave*. This depends on v_{crit} and t_{break}. If these two parameters are small, this congestion is clearly classified as several *Jam Waves* and no *Stop and Go*, because the speed drops are too far apart. If both parameters are set to their maximum, the congestion is classified as *Wide Jam*.

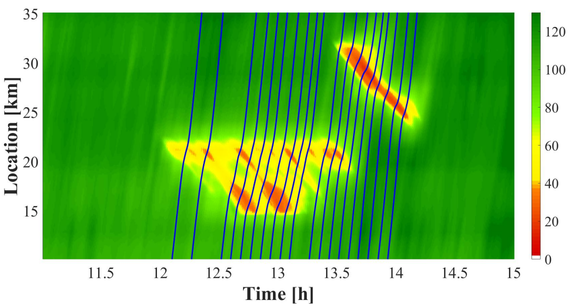

Fig. 10. Trajectories crossing the congestion types *Jam Wave*/*Wide Jam*

If all parameters are set to their maximum (n_{traj} set to its minimum to receive a maximal temporal distance of starting trajectories), the entire classification is unreliable. Congestion types often are only reported by single trajectories and these could pass the congestion anywhere. All parameters set to their minimum, just two of all considered congestion patterns changed the class compared to the consideration with base values. As described above, the congestion in Fig. 9 changes the type by varying the number of speed drops. While $n_{StopandGo}$ decreases, the type changes from *Mega Jam* to *Stop and Go* waves. Also a few trajectories switch from *Jam Wave* to *Mega Jam* because the maximal duration of a jam wave is shorter than the base value.

In addition to this few evaluated congestions, data sets of 157 days are analyzed. The findings of the previously executed analysis are taken for this extended investigation. The number of speed drops $n_{StopandGo}$ is optimized to two. For the base setting, the following parameter values are set: $v_{crit} = 40$ km/h, $\Delta t_{JamWave} = 3$ min, $t_{break} = 4$ min, $\Delta t_{MegaJam} = 30$ min.

The parameters for the variation are chosen because of their impact to the classification. Additionally, a setting with all varied parameters set to their respective maximum and minimum is executed. The share of classified trajectories of the total amount of calculated trajectories is analyzed. The values and the results of the sensitivity analysis are shown in Tab. IV.

The variation of the velocity threshold influences the classification most but the distribution of the jam classes is the same. Every adjustment of the other parameters causes just small changes on the results. These changes appear in every class except of *Mega Jam* since this congestion is classified just in a very small amount of speed data sets. Considering Tab. IV, the congestion types *Jam Wave* and *Wide Jam* are controlled by setting the maximal duration of a jam wave $t_{JamWave}$

If all investigated parameters in this larger analysis are set to their maximum, also the time period between the trajectory starts is maximal, the results represent the distribution when the velocity threshold is maximal. This is also the case if all values are set to their minimum compared to the results when v_{crit} is also minimal. This shows that the biggest influence on the categorization is the threshold for the velocity v_{crit}.

E. Results

Some parameter variations effect the automated classification highly. The greatest effect on the classification can be achieved by the velocity threshold v_{crit}. The base values defined in [14] basically work out. The gap between one jam wave and several jam waves is filled by the *Stop and Go* class. The number of speed drops $n_{StopandGo}$ is decreased from 3 to 2. *Stop and Go* is the type of any congestion with more than one speed drop down. The additional parameter, the time shift of the trajectories, should at most amount to 5 min. The velocity threshold v_{crit} results in 40 km/h for the congestion definition. In Tab. V, all derived optimized parameters are presented.

V. Conclusion

This paper treats the definition of congestion and the automated classification into different congestion types using virtual trajectories. A congestion is defined whenever the speed progress of a trajectory falls below a threshold of 40 km/h. Four different congestion types have been identified: *Jam Wave*, *Stop and Go*, *Wide Jam*, and *Mega Jam*.

TABLE IV

RESULTS AND SETTINGS OF PARAMETER VARIATION OF 157 DAYS

Parameter	Value	Calculated Trajectories	Percentage of all calculated trajectories which detected: Congestion	Jam Wave	Stop and Go	Wide Jam	Mega Jam
Base setting		45216	6.78%	2.65%	1.10%	2.90%	0.09%
Velocity threshold v_{crit}	30 km/h	45216	3.65%	1.50%	0.36%	1.72%	0.07%
Velocity threshold v_{crit}	50 km/h	45216	8.92%	3.46%	1.29%	4.02%	0.14%
Maximal duration jam wave $t_{JamWave}$	2 min	45216	6.78%	2.12%	1.27%	3.28%	0.09%
Maximal duration jam wave $t_{JamWave}$	4 min	45216	6.78%	3.03%	1.27%	2.38%	0.09%
Minimal break between speed drops t_{break}	3 min	45216	6.78%	2.73%	1.26%	2.71%	0.09%
Minimal break between speed drops t_{break}	5 min	45216	6.77%	2.66%	1.27%	2.75%	0.09%
Number of trajectories per hour n_{traj}	60	226080	6.83%	3.09%	1.29%	2.70%	0.09%
Number of trajectories per hour n_{traj}	6	22608	6.76%	2.70%	1.22%	2.77%	0.09%
All values maximal with $n_{traj} = 6/h$		22608	8.99%	4.27%	1.26%	3.28%	0.15%
All values minimal with $n_{traj} = 60/h$		226080	3.69%	1.31%	0.84%	1.60%	0.07%

TABLE V

RESULTS OF OPTIMIZED PARAMETERS

Parameter	Optimized Value
Critical velocity v_{crit}	40 km/h
Maximal duration jam wave $t_{JamWave}$	3 min
Minimal break between speed drops t_{break}	4 min
Minimal duration mega jam $t_{MegaJam}$	30 min
Minimal number of speed drops $n_{StopandGo}$	2
Number of trajectories per hour n_{traj}	at least 12

For each of them, several parameters are needed to classify an occurring congestion situation as exactly one type. The derived parameter set after an optimization is depicted in Tab. V. Using these parameters, congestion types can be automatically classified for any spatio-temporally discretized speed values.

The next steps will be to extend the parameter study to various freeways with different data sets also derived from other sources than stationary detectors.

ACKNOWLEDGMENT

The authors want to thank Arne Kesting (former Transver employee) who supported the final report for BMW and his thoughtful ideas how to define congestion and the classifications. Furthermore, the authors would like to thank *Autobahndirektion Südbayern* for providing the data.

REFERENCES

[1] T. Reed, INRIX Global Traffic Scorecard 2018, February 2019.

[2] K. Bogenberger, G. Huber, Verkehr besser verstehen und Verkehrsprobleme optimal lösen, Politische Studien 452, Hanns Seidel Stiftung, 2013, https://www.hss.de/download/publications/PS_452_Internet.pdf.

[3] M. Randelhoff, Die drei Haupttheoreme der Stauforschung: Der Schmetterlingseffekt, unsichtbare Wellen (=Phantomstau) und die Tragik des Zufalls, https://www.zukunft-mobilitaet.net/3344/analyse/wie-entstehen-staus-phantomstau/, 2017.

[4] ASTRA Bundesamt für Strassen Schweizerische Eidgenossenschaft, 21.03.2019, https://www.astra.admin.ch/astra/de/home/themen/nationalstrassen/ verkehrsfluss-stauaufkommen/definitionen.html.

[5] G. Cookson, INRIX Global Traffic Scorecard 2017, February 2018.

[6] Bayerisches Staatsministerium für Wohnen, Bau und Verkehr, http://www.bayerninfo.de/, 11.03.2019.

[7] G. Morrison, TomTom Traffic Index 2017, February 2018.

[8] B. S. Kerner, H. Rehborn, Experimental Properties of Complexity in Traffic Flow, Physical Review E, 53, pp. R4275-R4278, May 1996, DOI:10.1103/physreve.53.r4275.

[9] J. Palmer, H. Rehborn, I. Gruttadauria, Reconstruction Quality of Congested Freeway Traffic Patterns Based on Kerner's Three-Phase Traffic Theory, International Journal on Advances in Systems and Measurements, April 2011, pp. 168–181.

[10] B. S. Kerner, The Physics of Traffic, 2004, Berlin-Heidelberg: Springer, ISBN 978-3-540-40986-1.

[11] B. Bursa, N. Gajic, M. Mailer, Classification of traffic jams on alpine motorways, Transport Research Arena TRA 2018.

[12] B. S. Kerner, Introduction to Modern Traffic Flow Theory and Control – The Long Road to Three-Phase Traffic Theory, 2009, Berlin-Heidelberg: Springer, DOI:10.1007/978-3-642-02605-8

[13] D. Helbing, M. Treiber, A. Kesting, M. Schönhof, Theoretical vs. Empirical Classification and Prediction of Congested Traffic States, The European Physical Journal B, Vol. 69 (4), April 2009, pp. 583-598, DOI:10.1140/epjb/e2009-00140-5.

[14] K. Bogenberger, Stauklassifizierung und Untersuchung des Zusammenhangs Verkehrsstärke und Verkehrszusammenbruch – Abschlussbericht, 2010.

[15] M. Treiber, D. Helbing, Reconstructing the spatio-temporal traffic dynamics from stationary detector data, January 2002, Cooperative Transportation Dynamics, 1,3.1-3.24.

[16] M. Treiber, A. Kesting, R. E. Wilson, Reconstructing the traffic state by fusion of heterogeneous data, Computer-Aided Civil and Infrastructure Engineering, 26 (6), November 2011, 408–419, DOI:10.1111/j.1467-8667.2010.00698.x.

[17] F. Rempe, P. Franeck, U. Fastenrath, K. Bogenberger, Phase-Based Smoothing Method for Accurate Traffic Speed Estimation with Floating Car Data, Transportation Research Part C: Emerging Technologies, Volume 85, December 2017, 644-663, DOI:10.1016/j.trc.2017.10.015.

[18] L. Kessler, B. Karl, K. Bogenberger, Spatiotemporal Traffic Speed Reconstruction from Travel Time Measurements Using Bluetooth Detection, submitted to IEEE ITSC 2019.

[19] L. Kessler, G. Huber, A. Kesting, K. Bogenberger, Comparing Speed Data from Stationary Detectors Against Floating-Car Data, IFAC PapersOnLine 51-9 (2018) 299-304, DOI:10.1016/j.ifacol.2018.07.049.