WEATHER IMPACTS ON TRAFFIC: FROM DATA TO MODELS

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OUTLINE

1 **Problem Statement**
   - Objective

2 **Contributions**
   - Quantification of weather effects
   - Integration into traffic modeling
   - Toward online applications: Bayesian filtering

3 **Conclusion and Perspectives**
   - Summary of contributions
   - Perspectives


**Plan**

1. **Problem Statement**
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PROBLEM STATEMENT

Proactive real-time traffic management systems involves a comprehensive knowledge of all elements impacting traffic conditions.

Bad weather conditions are well recognized as one important event which can severely impact traffic in terms of traffic operations and safety.

What weather events? The presented work focuses on the effects of rain on traffic.
# Impact of Adverse Weather on Traffic Operations

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<tr>
<th>Drivers’ Behaviour</th>
<th>Speed and acceleration ↘</th>
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<td>Time Headways ↑</td>
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<td>Spacing ↑</td>
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<td>Lane Changing</td>
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<td>Platooning ?</td>
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<th>Consequences on Mobility</th>
<th>Capacity ↘</th>
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<td>Traffic Volume ↘</td>
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<td>Speed Variation ↑</td>
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<td>Travel Time ↑</td>
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<td>Congestion severity ↑</td>
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IMPACT OF ADVERSE WEATHER ON SAFETY

- Rain, snow \(\rightarrow\) degradation of the state of the pavement, reduction of the visibility as well as light,
- Increase of the crash frequencies and above all crash severity,
- Lagged effect of precipitation across days: the effect of rain is higher if many days have passed since the last precipitation.
GLOBAL FRAMEWORK (TU0702 COST ACTION)
Objectives of our work are many-fold:

1. To quantify the effects of rain on traffic through empirical analyses,

2. To propose a global modelling framework based on a Vlasov formulation with original numerical approaches (Lagrange+remap scheme),

3. To illustrate the influence of the models’ parameters on the numerical solutions,

4. To move toward weather-responsive traffic management with traffic state estimation.

**Bottom line**

The goal is to introduce the effects of weather into traffic modelling
PLAN

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   - Summary of contributions
   - Perspectives
Part I: Quantification of Weather Effects
GENERAL FRAMEWORK

DATA FUSION & DATA SELECTION

Selection of relevant data subsets with similar characteristics (traffic composition, type of day, lane)

- Traffic data
- Weather data
- Dataset 1: No rain
- Dataset 2: Light rain
- Dataset 3: Medium rain
- Dataset N: Heavy snow

DATA MINING

- MESOSCOPIC ANALYSIS (Platoons)
- MICROSCOPIC ANALYSIS (Time headways, Spacing, Individual Speeds)
- MACROSCOPIC ANALYSIS (Free Flow Speed, Capacity, Critical Density)
Example: Time Headways (TIV)

**Figure:** Time headways distribution (RN118).
LOG-NORMAL MODELING
**Impact on Fundamental Diagram**

**Figure:** Van Aerde Model. Fast lane, cars. RN118 data.
FUNDAMENTAL DIAGRAM PARAMETERIZATION
PART II: INTEGRATION INTO TRAFFIC MODELING
MODELING SCALES

Mesoscopic modelling

Microscopic modelling
- Follow-the-leader
- Cellular automata

Macroscopic modelling
- Fokker-Planck, Vlasov
- first order models
- second order models
What level should we choose to integrate weather effects?

- First, FD parameterization enables the integration into LWR model,
- But a second order modeling brings benefits for it takes into account uncertainty better
  - Idea: to start from a general Vlasov equation in order to derive macroscopic equations.
We start from a general Vlasov kinetic equation at a mesoscopic level:

\[
\partial_t f + \partial_x (vf) + \partial_v \left( a(v, f, \partial_x f) f \right) = \eta(f) \left( f^{eq} - f \right),
\]

(1)

where \( f = f(x, v, t) \) is the density of vehicles having speed \( v \) at position \( x \) at time \( t \), \( f^{eq} = f^{eq}(f) \) is an equilibrium density function, \( \eta(f) \geq 0 \) is a relaxation rate towards the equilibrium, \( a(v, f, \partial_x f) f \) is an acceleration term.
How to derive macroscopic equations from the meso level?

- Application of the methods of moments yields macroscopic equations.
- The resulting model form only depends on some closures (parameters choices).
- Possibility to derive a hierarchy of models from a mesoscopic one.
We obtain the following two-equation system, in which we can introduce a meteorological parameter $\mu$ corresponding to the rain intensity in $mm/h$.

\[
\partial_t \rho + \partial_x (\rho u) = 0, \tag{2}
\]

\[
\partial_t (\rho u) + \partial_x (\rho u^2) - \partial_x \left( \frac{1}{2} \rho \rho_0 u^2 \right) = \rho \eta(\rho, u) (u^{eq}(\rho) - u). \tag{3}
\]
TWO-EQUATIONS MACROSCOPIC MODEL

We obtain the following two-equation system, in which we can introduce a meteorological parameter $\mu$ corresponding to the rain intensity in $mm/h$.

\[
\frac{\partial}{\partial t} \rho + \frac{\partial}{\partial x} (\rho u) = 0,
\]

\[
\frac{\partial}{\partial t} \rho u + \frac{\partial}{\partial x} (\rho u^2) - \frac{\partial}{\partial x} \left( \frac{1}{2} \rho_0 u^2 \right) = \rho \eta(\rho, u, \mu) (u^{eq}(\rho, \mu) - u).
\]
MODEL PROPERTIES

- Hyperbolic structure close to Aw-Rascle or Zhang models,
- Original closures for the acceleration and relaxation rates.

Linear stability analysis for two forms of the relaxation term:

- Case 1: classical relaxation term: conditionally linearly stable depending on $\rho_0$.

\textbf{Cas 1 : Théorème}

The system is linearly stable towards a steady state $(\rho, u^{eq}(\rho))$ if and only if

$$-\rho^2 (u^{eq})'(\rho) \leq \rho_0 u^{eq}(\rho).$$

(4)

- Cas 2: quadratic relaxation term, linearly stable.
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\[-\rho^2 (u^{eq})'(\rho) \leq \rho_0 u^{eq}(\rho).\]  \hspace{1cm} (4)

- Cas 2: quadratic relaxation term, linearly stable.
Numerical discretization

We consider an uniform subdivision of the space: \( \{x_j\}_{j \in \mathbb{Z}}, \ x_j = jh \) where \( h \) is a constant space step.
From discrete sequences of densities \( (\rho_j^n)_{j \in \mathbb{Z}} \) and speeds \( (u_j^n)_{j \in \mathbb{Z}} \) at time \( t^n \), we want to compute the quantities at time \( t^{n+1} = t^n + \Delta t^n \), \( \Delta t^n > 0 \).

- Fractional step method to solve separately the homogeneous part of the system and the source term.
- Lagrange+remap scheme for the homogeneous part.
FRACTIONAL STEP METHOD

1. Over $\Delta t^n/2$ :

$$\frac{\partial}{\partial t} \begin{pmatrix} \rho \\ \rho u \end{pmatrix} + 0 = S. \quad (5)$$

2. Over $\Delta t^n$, Lagrange+remap :

$$\frac{\partial}{\partial t} \begin{pmatrix} \rho \\ \rho u \end{pmatrix} + \frac{\partial}{\partial x} \begin{pmatrix} \rho u \\ \rho u^2 - \frac{1}{2} \rho_0 u^2 \end{pmatrix} = 0. \quad (6)$$

3. Over $\Delta t^n/2$ :

$$\frac{\partial}{\partial t} \begin{pmatrix} \rho \\ \rho u \end{pmatrix} + 0 = S. \quad (7)$$
LAGRANGE REMAP SCHEME

- **Lagrange step**: mass and mass movement conservation in a cell $j$

  \[
  h_{j}^{(2)} = h + \Delta t^n \left( u_{j+1}^{(1)} - u_{j}^{(1)} \right). \\
  \rho_j^{(2,\star)} = \frac{h}{h_j^{(2)}} \rho_j^{(1)}.
  \]

  \[
  u_j^{(2,\star)} = u_j^{(1)} + \frac{\rho_0 \Delta t^n}{2h\rho_j^{(1)}} \left( (u_{j+1}^{(1)})^2 - (u_j^{(1)})^2 \right). 
  \]

- **Projection step**: The remap phase is used to reproject the convected discrete onto the initial Eulerian mesh.

  \[
  \rho_j^{(2)} = \nu_{j-1/2} \rho_{j-1}^{(2,\star)} + (1 - \nu_{j-1/2}) \rho_j^{(2,\star)},
  \]

  \[
  (\rho_j u_j)^{(2)} = \nu_{j-1/2}(\rho_{j-1} u_{j-1})^{(2,\star)} + (1 - \nu_{j-1/2})(\rho_j u_j)^{(2,\star)}, \quad u_j^{(2)} = \frac{\rho_j u_j^{(2)}}{\rho_j^{(2)}}.
  \]
ILLUSTRATION OF THE PROJECTION

Figure: Projection
TEST CASE 1: LINEAR INSTABILITY

- We consider a spatial domain $D = [0, 1]$ with periodical boundary conditions,
- Uniform mesh of 800 points, CFL number equal to 0.45,
- DF: triangular law with following parameters: $\rho_M = 250$ veh/km, $\rho_c = 50$ veh/km and $u_f = 130$ km/h.
- For the first test case, the parameters are chosen so that the linearly unstable region corresponds to the densities so that $u^{eq}(\rho) < \frac{u_f}{2}$.
GROWTH OF LINEAR INSTABILITIES

For the first test case, the parameters are chosen so that the linearly unstable region corresponds to the densities so that $u_{eq}(\rho) < \frac{u_f}{2}$. The next figure shows the growth in time of the linear instabilities from a small initial perturbation (Riemann-like problem initialisation):

**Figure**: Growth of the linear instabilities in the dense region $\alpha = 0$. Profile of the mean densities and speeds, (a) at time $t = 0.002$ and (b) at time $t = 0.1$. 
**Test Case 2: Non Linear Instabilities and Effects of the Relaxation Parameter**

Although the system is linearly stable, instabilities develop in the dense traffic region.
Test case 2: non linear instabilities and effects of the relaxation parameter

**Figure:** Effect of the relaxation parameter, case $\alpha = 1$. Profiles of mean densities and speeds at time $t = 1$, (a) for $\ell = 10^{-7}$, (b) for $\ell = 10^{-6}$, (c) for $\ell = 10^{-5}$ and (d) for $\ell = 10^{-4}$.
MODEL BEHAVIOUR FACED WITH CHANGING WEATHER CONDITIONS

**Figure:** Short relaxation time: density and speed profile at time $t = 0.015$. 
FROM DRY TO RAINY WEATHER: FROM UNCONGESTED TO CONGESTED REGIMES
FROM DRY TO RAINY WEATHER: FROM UNCONGESTED TO CONGESTED REGIMES
Weather dependent relaxation rate: non linear instabilities in the dense traffic regime, (a) at time $t = 0.015$ and (b) at time $t = 0.03$. 

**Figure:** Weather-dependent relaxation rate: non linear instabilities in the dense traffic regime, (a) at time $t = 0.015$ and (b) at time $t = 0.03$. 

**Problem Statement**

**Contributions**

**Conclusion and Perspectives**

**Quantification of weather effects**

**Integration into traffic modeling**

**Toward online applications:** Bayesian filtering
Part III: Toward Online Applications: Bayesian Filtering
Traffic state estimation

- Estimating traffic state in real time is valuable in terms of traffic surveillance and control,

- **Goal**: estimation of the macro variables (flow, densities) along a road section, based on all available measurements.

Traffic state estimation is based on two concepts:

- A macroscopic model to describe traffic dynamics
- An estimation method to update the different states of the dynamic system.
Traffic state estimation

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- A macroscopic model to describe traffic dynamics
- An estimation method to update the different states of the dynamic system.
**Traffic State Estimation: Model**

- First order cell version of LWR model,
- Model written in a numerical discrete version at a section level. The motorway section is divided into $n$ cells.

**Figure:** Section discretization
Godunov’s numerical scheme: discretized version of the conservation equation and balance equation:

1. **Conservation Equation:**

   \[ k_i(t + \Delta t_N) = k_i(t) + \frac{\Delta t_N}{\Delta x_i} (q_{i-1}(t) - q_i(t)) \]  

2. **Balance:** \[ q_i(t) = \min (\Delta_i(t), \Omega_{i+1}(t)) \]
Godunov’s numerical scheme: discretized version of the conservation equation and balance equation:

1. Conservation equation:

\[ k_i(t + \Delta t_N) = k_i(t) + \frac{\Delta t_N}{\Delta x_i} (q_{i-1}(t) - q_i(t)) \]  \hspace{1cm} (8)

2. Balance: \( q_i(t) = \min (\Delta_i(t), \Omega_{i+1}(t)) \).
Traffic state estimation : variables

State vector
State vector to be estimated at time $t$ consists of flows and densities in the $n$ cells of the section. Integrating the upstream demand $q_0$, the vector of size $2n + 1$ is written:

$$x_t = (k_1(t), ..., k_n(t), q_0(t), ..., q_n(t))^T.$$  \hspace{1cm} (9)

State equation
With $u_t$ being the system inputs, the state equation consists of estimating the state vector at time $t + 1$

$$x_{t+1} = f(x_t, u_t).$$  \hspace{1cm} (10)
Traffic state estimation : filtering approach

The goal is to achieve an estimation of the state vector starting from the measurements performed on the system.
In the Bayesian framework, dynamic traffic state estimation is carried out through the construction of the posterior probability density function (PDF) \( P(x_k|y_{0:k}, u_{0:k-1}) \). A Bayesian recursive formula is derived:

\[
P(x_k|y_{0:k}, u_{0:k-1}) = P(x_{k-1}|y_{0:k-1}, u_{0:k-2}) \times \frac{P(y_k|x_k) \times P(x_k|x_{k-1}, u_{0:k-1})}{P(y_k|y_{k-1}, u_{0:k-2})}
\] (11)

The formula above is only theoretical. Need of estimation methods to compute the posterior density function (cannot be solved analytically).
A sequential Monte Carlo state observer is used to estimate the state vector and then to derive travel time estimations.

- In Sequential Monte Carlo Methods (particle filters), the posterior probabilities are represented by a set of randomly chosen weighted samples.
- On each time step, new samples are generated and the weights updated.
- Other filtering methods: extended Kalman filters, ensemble Kalman filters.
GAUSSIAN STATE SPACE CASE

With the previous model:

\[ x_k = f(x_{k-1}, u_{k-1}) + w_{k-1} \]  \hspace{1cm} (12)
\[ y_k = Cx_k + v_k \]  \hspace{1cm} (13)

where we have assumed that the uncertainties are gaussian and have zero means:

\[ w_k \propto N(0, Q_k) \]  \hspace{1cm} (14)
\[ v_k \propto N(0, R_k) \]  \hspace{1cm} (15)

We are in a Gaussian state space case (Doucet, 1998), which simplifies the updates of the weights (no need of importance sampling methods)
GAUSSIAN STATE SPACE CASE (2)

Denoting

\[
S_k^{-1} = Q_k^{-1} + C^t R_k^{-1} C
\]

\[
\mu_k = S_k \left( Q_k^{-1} f(x_{k-1}, u_{k-1}) + C^t R_k^{-1} y_k \right)
\]

One can obtain

\[
P(x_k | x_{k-1}, u_{k-1}, y_k) \propto N(\mu_k, S_k)
\]

\[
P(y_k | x_{k-1}, u_{k-1}) \propto \exp\left( -\frac{1}{2} (y_k - Cf(x_{k-1}, u_{k-1}))^t (R_k + CQ_k C^t)^{-1} (y_k - Cf(x_{k-1}, u_{k-1})) \right)
\]

And the updates of the weights at time \( k \) take the following form

\[
w_k^i \propto w_{k-1}^i P(y_k | x_{k-1}^i, u_{k-1})
\]

the weights being afterwards normalized such that \( \sum_i w_k^i = 1. \)
APPLICATION TO REAL WORLD DATA

8 sensors on a Lyon's ring road section in north-south direction.

FIGURE: Discretisation de la section
RESULTS WITH RAIN INTEGRATION (1/2)

Simulation of a rain event over the whole section between 6 and 10am

PROOF OF CONCEPT
The goal is to show the possible estimation errors if only one fundamental diagram is used.
1. Without rain in the model
1. Without rain in the model

⇒ Estimation errors (6-10h)
1. Without rain in the model

$$\Rightarrow$$ Estimation errors (6-10h)

2. Weather dependent FD
1. Without rain in the model

⇒ Estimation errors (6-10h)

2. Weather dependent FD

⇒ Correct estimations
Plan

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SUMMARY (1/2)

Quantification of weather effects

- Multilevel assessment,
- Application to a huge amount of data,
- First results basis for interurban sections in France and Europe.

Traffic modeling (1/2)

- New two-equation model derived from a Vlasov equation,
- Fractional step method and Lagrange+remap scheme for numerical discretization.
SUMMARY (2/2)

**Traffic modeling (2/2)**
- Numerical tests validate theoretical properties,
- Potential of second order models faced with changing weather conditions.

**Traffic estimation**
- Development of particle filtering for traffic state estimation,
- Application to real world data,
- Results show benefits of a weather-responsive traffic management.
Perspectives (1/2)

On the weather effects...

- Need for new data in order to study different events (heavy rain, snow, fog, visibility),
- Platoon analyzes under adverse weather conditions,
- Drivers’ behavior at the beginning of a rain event,
- Effects in urban areas (ex: signal timing).
**PERSPECTIVES (2/2)**

**ABOUT TRAFFIC MODELING**
- Deep analysis at a mathematical level,
- Validation with real rainy data,
- Comparison with other models from this family,
- Comparaison of Lagrange-remap approaches with other methods.

**ON ESTIMATION**
- Performances comparison with other estimation methods: extended Kalman, ensemble Kalman etc.,
- Comparison second order model/Kalman method with LWR/MCS.
Journals:


Publications (2/2)

International conferences:


BILLOT, R., Integrating the effects of adverse weather on traffic: methodology, empirical analyses and simulation. *Young researcher seminar 2009*, Torino (Italie), 5-9 June 2009.


Thank you