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Comparison of different approaches to predict air pollution inside the tunnel tube

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ABSTRACT
This paper deals with models of air pollution inside a tunnel tube. Various gases are emitted by combustion engines. They consist largely of oxides of nitrogen, carbon monoxide, steam and particles (opacity). Since each tunnel is unique, the design of the model must be realized for the particular road tunnel. Data measured in the control center of the tunnel is used to create various models and to realize them in the program environment MATLAB. It is possible to describe this system by description of the equations of physical dependences. These physical dependencies are between the speeds, piston effect, traffic density, quantity produced pollution, etc. Next we plan to show how fuzzy sets can be used to represent a real system. Finally, we are going to describe this system by the parametric model. For the purpose of parametric identification it is interesting to describe the sought process using input-output relations. The general procedure for estimation of the process model consists of several steps: determination of the model structure, estimation of parameters and verification of the model.

KEYWORDS: system modeling, predictions, motor vehicle air pollution, parametric model, multivariable identification

1. Introduction

Models have a very important role in control system design and implementation. Models can be used to simulate the expected process behavior with a proposed control system. In the development of a dynamic model, simplifying assumptions are often made. The model requirements are a function of the usage of the model. The system is the tunnel tube. Emissions from cars are determined not only by the way they are built, but also by the way they are driven in various traffic situations. Gases emitted by combustion engine consist largely of oxides of nitrogen (NOx), carbon monoxide (CO), steam (H2O) and particles (opacity). We are going to describe the dynamic behavior of the system. Relation between traffic intensity, vehicle velocity and air velocity is also needed to describe this system. In this paper we pointed out to concentration of CO, NOx and opacity inside the tunnel tube, because this type of pollution is most dangerous for human organism. Using the model we can predict concentration of CO, NOx and Opacity. Dangerous limit for CO concentration is 75 ppm. The recommended maximum safe CO concentration is 10 ppm (parts per million). Most people do not experience symptoms below 75 ppm, but above this concentration the exposure can cause headaches, fatigue and nausea. The abbreviation ppm is a way of expressing very dilute concentrations of substances. Just as per cent means out of a hundred, so parts per million or ppm means out of a million. It describes the concentration of something in the air.

2. System modeling

By the term system an object in which variables of different kinds interact and produce observable signals is described. System identification is the study of modeling dynamic systems from experimental data.

System (S): A defined part of the real world. Interactions with the environment are described by input signals, output signals and disturbances.

Model (M): A description of a system. The model should capture the essential behavior of the system.

Inputs values are traffic intensity, velocity, pressure and output values are CO (carbon monoxide) concentration, NOx (oxides of nitrogen) concentration and opacity inside the tunnel. Traffic rate of cars and trucks, their speed, the concentrations of CO, NOx and Opacity must be available. These data is measured directly by sensors inside the tunnel tube. Traffic intensity is sensed by a camera system and the vehicles are then counted and sorted by categories in database system. More information about monitoring of the traffic can be found in [7] and [12]. The security of transferring the data is discussed in [6] and [13]. Technical support of traffic control system is discussed in [8].

2.1 Simulations based on the movement of air

All calculations represent a significant simplification of the actual situation. Turbulence, diffusion of pollutants, pressure gradients and local factors are not taken into the account. The principle of the calculation is based on the idea that powers that affect to the air mass in the tunnel must be in balance [4]. These powers are:

1. tractive power of the jet fans (N_{vent});
2. tractive power of vehicles (N_{voz});
3. wind force;
4. pressure drop caused by chimney effect;
5. resistance inside the tunnel acting upstream the direction of the prevailing airflow.

To simulate normal operation of the tunnel we use Bernoulli equation. These are based on the law of conservation of energy and appropriate adjustments we can come to the form, which leads to a steady-state pressure drop inside the tunnel tube. Calculation based on impulse equation where moment of force being equal to momentum

$$m \cdot v = N \cdot t \tag{1}$$

where N is the sum of the forces acting m is the mass of the air mass in the tunnel. In the simplest case, the power is acting tractive power of fans. Assumes that the initial velocity of the air is zero; in the absence of resistance tunnel tube is valid:

$$mv_T = N_{vent} t \tag{2}$$

where m is the mass of air in the tunnel tube. For the speed $\underline{v}_T$ is valid:

$$v_T = \frac{1}{m} N_{vent} t \tag{3}$$

and in differential form:

$$dv_T = \frac{1}{m} N_{vent} dt \tag{4}$$

This means that in the absence of resistance tunnel tubes would run the fan speed of the air soared to infinity. In practice this is not possible, after some time there is a balance, which is equal to the resistance of the tunnel fan traction force. Resistance has a dimension of power [kg.m.s^{-2}]. For the tunnel tube resistance following relation holds:

$$N_T = F_T \zeta_T \frac{\rho}{2} v_T^2 \tag{5}$$

Calculation of tractive force vehicles:

For the pulling power vehicles we have relation:

$$N_{voz} = \frac{M \cdot L_T \cdot \rho \cdot c_v F_v}{v_v \cdot 3600 \cdot 2} \left(v_v - v_T \right)^2 \tag{6}$$

and is valid that:

$$mv_T = N_{voz} t - kv_T^2 \tag{7}$$

where k denotes the resistance of the air in the tunnel tube, we must the equation on the right side divided by the mass of air in the tunnel. We get [4]:

$$dv_T = \left(\frac{M \cdot c_v F_v}{F_T \cdot v_v \cdot 3600 \cdot 2} \left(v_v - v_T \right)^2 - k_2 v_T^2 \right) dt \tag{8}$$

In Fig. 3. we can see the simulation of the air velocity inside the tunnel tube at different vehicle speeds of the vehicles and intensities.

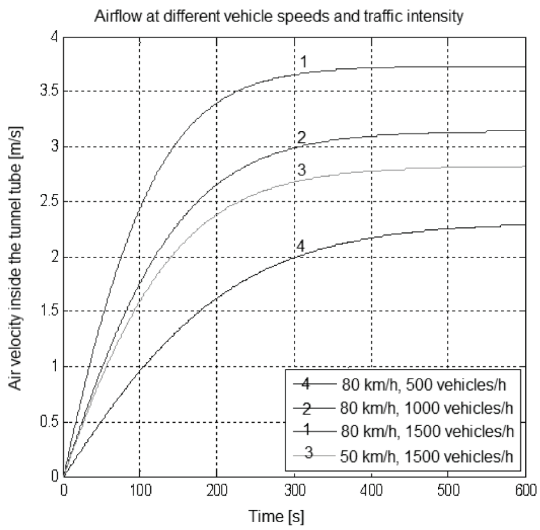

Fig. 1. Simulation of the air velocity inside the tunnel tube at different vehicle speeds of the vehicles and intensities

This method describes all dependences as not accurate, because this system has most stochastic behavior. We need more information to describe, how the airflow affects dangerous gases.

2.2 Simulations based on the fuzzy model

Fuzzy logic provides a convenient method to implement such knowledge into computers. This logic is the concept of fuzzy sets [2] incorporated into the framework of multivalued logic. The models expressed by this concept are called fuzzy models. Today, fuzzy models are widely employed. They cover a wide range of applications. Unfortunately, the identification of fuzzy models is a very complex task that comprises the identification of:

a. the input and output variables,
b. the rule base,
c. the membership functions and
d. the mapping parameters.

Thus, we face an optimization task with many local minima. The complexity of this task was shown for instance in [9].

Fuzzy systems have very strong functional capabilities. That is, if properly constructed, they can perform very complex operations. Actually, many fuzzy systems are known to satisfy the "universal approximation property" [2]. We use bisector as defuzzification method, product for the premise and implication, and Trim and Gaussian membership functions. Name this fuzzy system $f(u)$. Then, for any real continuous function $\psi(u)$ defined on a closed and bounded set and an arbitrary $\varepsilon > 0$, there exists a fuzzy system $f(u)$ such that

$$\sup_u |f(u) - \psi(u)| < \varepsilon. \tag{9}$$

where "sup" denotes the "supremum". Note, however, that all this "universal approximation property" does is guarantee that there exists a way to define the fuzzy system $f(u)$ (e.g., by picking the membership function parameters). It does not say how to find the fuzzy system, which can, in general, be very difficult. Furthermore, for arbitrary accuracy you may need an arbitrarily large number of rules. The rule-base with a large number of rules will require a long time period for the learning mechanism to fill in the correct control laws since smaller portions of the rule-base map should be updated by the FMRLC (Fuzzy Model Reference Learning Control) for a higher granularity rule-base [3]. In the Fig. 2 we can see the simulation based on input data with comparison by measured values in real system.

2.3 Simulations based on the parametric models

system identification is the study of modeling dynamic systems from experimental data. The system Identification procedure:

a. Collect Data. If possible choose the input signal such that the data are maximally informative.
b. Choose Model Structure. Use application knowledge and engineering intuition. Most important and most difficult step (don't estimate what you know already).
c. Choose the identification approach. How would a good model look like?
d. Choose best model in model structure (optimization or estimation).

For the purpose of identification it is interesting to describe the sought process using input-output relations [11]. The general procedure for estimation of the process model consists of several steps: determination of the model structure, estimation of parameters and verification of the model. Finally we can convert the created models to any other usable form.

State-space model can be used to describe the dynamics of system with initial conditions. The concept of the state of a dynamic system refers to a minimum set of variables, known as state variables that fully describe the system and its response to any given set of inputs.

For Multiple-input Multiple-output system we can write the transfer function matrix by parametric system identification method. The discrete transfer function (TF) matrix, $G(z)$, relates the Z transform of the response vector to the Z transform of the excitation vector for zero initial conditions.

$$\mathbf{Y}(z) = \mathbf{G}(z)\mathbf{U}(z) \tag{10}$$

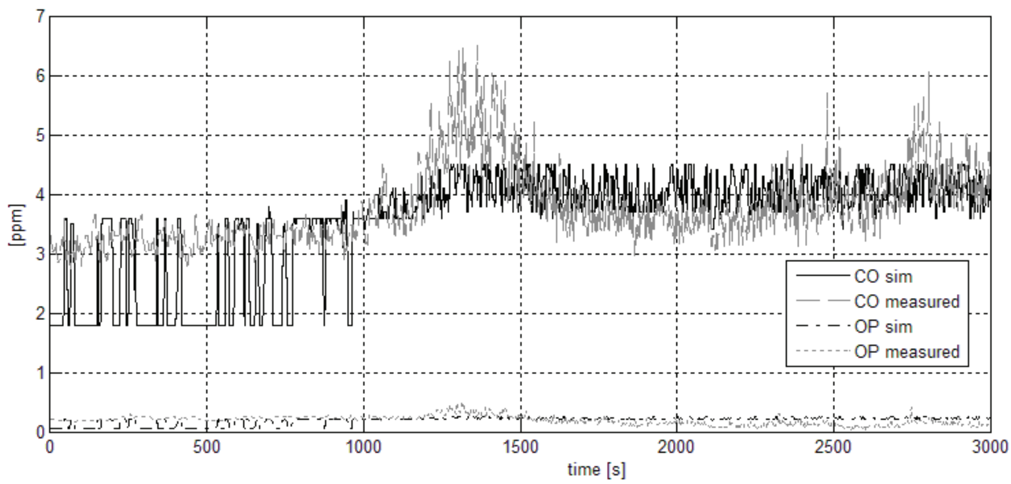

Fig. 2. Simulation of CO and OP concentrations inside the tunnel tube based on fuzzy model (black and black dashed values) in comparison with measured data (the values in gray dashed and gray dotted)

where;

$$\mathbf{Y}(z) = \mathrm{Z}\left[y_1(k), y_2(k), \ldots, y_m(k)\right]^{\mathrm{T}};\ y_i(k) = i\text{th output} \quad (11)$$

$$\mathbf{U}(z) = \mathrm{Z}\left[u_1(k), u_2(k), \ldots, u_n(k)\right]^{\mathrm{T}};\ uj(k) = i\text{th output} \quad (12)$$

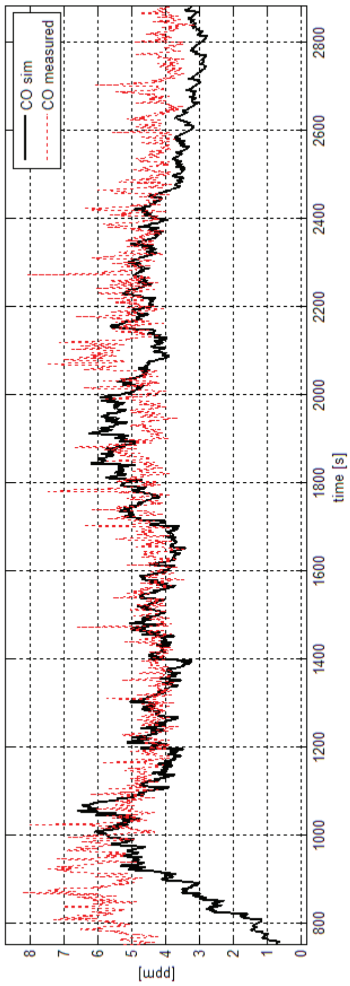

Fig. 3. Comparison of the simulation based on parametric model (black line) with the real measured data of CO inside the tunnel tube

As we can see in Fig. 3. simulation based on this type of model does not allow compute with the initial condition. Although the simulated value is not the same as measured data this result is sufficient for this system with most stochastic behavior. Another approach using the mathematical model is described in [5].

3. Predictions

Based on these models, we can make predictions to the future. Predictions of CO concentration with the parametric model is shown in Fig. 4.

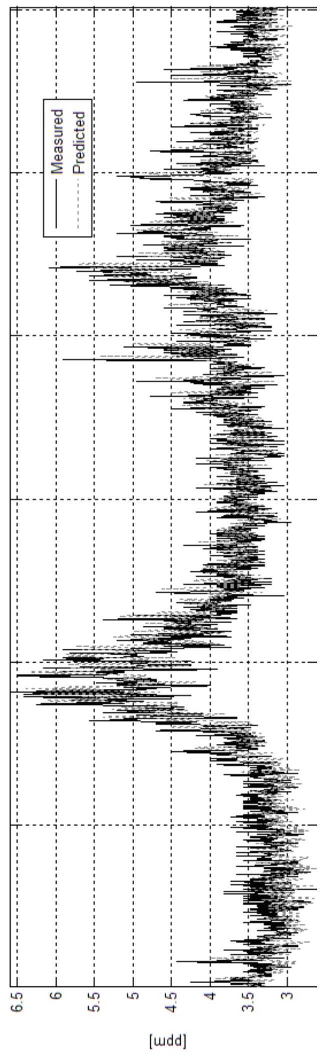

Fig. 4. Twenty minutes predictions based on parametric model (black line) with the real measured data inside the tunnel tube

Prediction can be realized with any time horizon. The similarity of the measured and predicted values is in the range from 50 to 70%, but for the system with a strong stochastic behavior these results are excellent. According to the predicted values we can see that the peaks of the measured values are substantially eliminated.

4. Conclusion

The objective of this work was to evaluate the models suitable to demonstrate the dynamic behavior of the real system. Numerical modelling studies based on measured data have been used to evaluate the level of pollution to the future according to real time data. These results can be used as a support for control of the traffic in the tunnel control center.

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