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AUTOMATIC IDENTIFICATION OF TUNING PARAMETERS OF BRAKE PIPE PNEUMATIC MODEL

G. Arcidiacono, P. Placidoli
Department of Innovation and Information Engineering
Marconi University, Via Plinio 44, Rome, 00193, Italy

L. Cantone
Department of Engineering for Enterprise “Mario Lucertini”
University of Rome “Tor Vergata”, Via del Politecnico 1, Rome, 00133, Italy

ABSTRACT

Paper shows the basic concepts for an automatic identification procedure of several parameters of a brake pipe pneumatic model. The procedure is on a hybrid metaheuristics scheme that involves the radial basis functions. Automatic procedure is applied to pneumatic module of TrainDy, UIC software for computation of Longitudinal Train Dynamics (LTD) of freight train. Such pneumatic module has been validated by a manual identification of parameters in order to create a device library of the most commonly used braking devices of European freight trains. Results show the reduction of the error by means of this procedure that could be further improved to consider also other aspects, such as the local curvature of time evolution of air pressure in brake pipe.

Keywords: freight trains, brake pipe pneumatics, model parameters identification, Longitudinal Train Dynamics (LTD), DOE, Optimization.

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1. INTRODUCTION

Freight trains provide an efficient and environmentally sustainable way to move goods from a place to another [1]. Increasing the tonnage of freight trains is a way to improve the economic efficiency of freight transportation. Anyway, it is practical experience that in-train forces also increase with train tonnage (keeping fixed the other parameters). Main reason for this behaviour is the intrinsic functioning of braking systems that equip freight trains, which do not guarantee the same braking power of different wagons, causing in-train forces because of different braking accelerations of consecutive wagons. Longitudinal Train Dynamics (LTD) covers, among the others, this issue and [2] reports a recent review on this topic. Addressing LTD is important in order to increase trains hauled mass in a safe way, i.e. avoiding train derailments (caused by high in-train compressive forces [3]) and train disruptions (caused by high in-train tensile forces). At this aim, it is necessary to compute the braking forces, the operational forces (such as forces applied at traction units, running resistance forces, and so on) and in-train forces.

The normal force and the friction coefficient between wheel and shoe (for block brakes) or between disc and pad (for disc brakes) are two key parameters to determine braking force acting on the wagon. Depending on friction material, the relationship between friction coefficient, speed and normal force changes and humidity, temperature, wear also affect its value. Wagon braking design and air pressure in brake cylinder mainly determine braking force. Air pressures in brake pipe and control valve (or distributor) regulate the air pressure in brake cylinders.

First studies on air pressure in trains braking systems have been carried out in 1970s in the United States. Further studies [4] have been performed in Japan on air pressure in brake pipe in 1980s. In the same years, an application to freight trains of the pneumatic model developed in [5] can be found in [6] and in [7]. These models, however, do not explicitly consider any section variation along the pipe and equivalent loss coefficients or an increasing of the total pipe length account for the localized pressure losses at each flexible coupling between consecutive wagons. Unfortunately, both procedures imply non-negligible negative effects related to the non-physical modelling of the system that, even if properly tuned for one particular configuration, can be completely misleading for a different set-up.

As already developed by the authors in other works [8], in literature many holistic approaches are able to simulate engineering problems. Studies that are more recent have been carried out in South Korea, Poland, Italy and China with different levels of accuracy and broadness of application [9-13]. This paper is based on pneumatic model introduced in [14], which has been specifically designed for UIC braking scheme and has been incorporated in a software, called TrainDy, which is able to numerically solve the LTD [15] and has been validated in [16-17] too. In order to perform LTD studies in an operative way, it is important to have a tool, which is capable to address both pneumatic and dynamic problem at the same time. This allows statistical investigations, as those performed in [18] and requested for international freight traffic in Europe, by [19]. Topic of statistical investigation of performance of a freight train is complex and has been addressed, among the others, in [20-21].

The paper shows the results of a first study on how to perform an automatic identification (or calibration) of the characteristic parameters that govern the emptying of brake pipe, comparing the results against two experimental tests from Trenitalia and Deutsche Bahn AG (DB AG), already used in [15].

2. BRAKE PIPE PNEUMATIC MODEL

Before addressing the main topic of the paper, it is worthwhile a quick recall to the basics of UIC braking scheme, which equips the majority of European freight trains ([21]). 0 shows the main components of this braking system: figure reproduces the braking system of a traction unit followed by one wagon. Compressor (9) produces compressed air able to fill up the General Pipe or Brake Pipe (1), by means of the Main Reservoir (10). During braking application, the Driver's Brake Valve (11) spills out the air from the Brake Pipe (BP); this air pressure reduction activates the Control Valve (4) that fills the Brake Cylinder (7) by spilling air from the Auxiliary Reservoir (5). Within the Control Valve, there is an Accelerating Chamber (a small volume) which accelerates the venting of brake pipe during a braking.

Trains with distributed power/braking have more traction units distributed along the train, hence they have more Driver's Brake Valves, i.e. points that can spill out or blow in air respect to brake pipe. As previously said, [14] introduces an effective numerical model to compute the air pressure in BP: the model simplifies the airflow in BP by means of a quasi mono-dimensional approach. For Readers' convenience, this paper briefly recalls this model. The BP is modelled as an elongated circular pipe with variable cross section, at initial pressure P_{ini}, from which air can be blown in or spilled out with a mass flux, called $\dot{m}$. The pipe has a constant diameter within each vehicle and a diameter variation at flexible connection between two consecutive vehicles (hose couplings).

From the conservation of mass and energy and the balance of momentum, within the above hypotheses, the governing equations become:

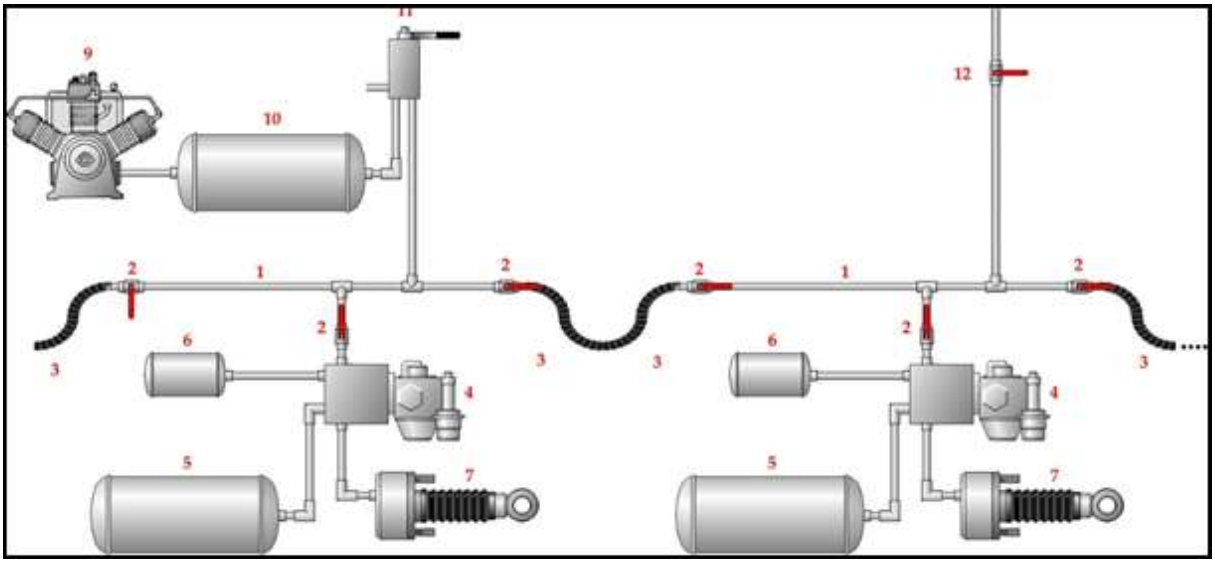

Figure 1 UIC braking system scheme.

$$\begin{cases} \dfrac{\partial \rho}{\partial t} + u\dfrac{\partial \rho}{\partial x} + \dfrac{\rho}{S}\dfrac{\partial (uS)}{\partial x} = -\dfrac{\dot{m}}{Sdx} \\ \dfrac{\partial u}{\partial t} + \dfrac{1}{\rho}\dfrac{\partial p}{\partial x} + u\dfrac{\partial u}{\partial x} = \dfrac{\tau}{D} + \dfrac{u}{\rho}\dfrac{\dot{m}}{Sdx} \\ \dfrac{\partial q}{\partial t} + u\left(\dfrac{\partial q}{\partial x} + r\dfrac{\partial T}{\partial x}\right) + r\dfrac{T}{\rho S}\dfrac{\partial (\rho u S)}{\partial x} = 4\dfrac{\phi_T}{\rho D} - \dfrac{\tau u}{D} - \dfrac{\dot{m}}{Sdx}\dfrac{1}{\rho}\left[(c_v + r)T_l + \dfrac{1}{2}u_l^2 - q\right] \end{cases} \quad (1)$$

Where ρ is the density, u axial velocity, p pressure, T temperature and all of them must be considered as mean values on the general cross-section S of diameter D and abscissa x; q is the specific energy, c_v is the specific heat at constant volume, $\tau = -\mathrm{sgn}(u)\cdot\left(f + K\cdot\dfrac{D}{dx}\right)\cdot\dfrac{u^2}{2}$ takes into account the dissipative sources (there, f is the distributed coefficient of pressure loss, K is the concentrated coefficient of pressure loss and $sgn(\cdot)$ is the sign function); ϕ_T is the exchanged thermal flux, r is the gas constant; lastly, subscript l refers to lateral quantities, which has to be computed by imposing the right boundary conditions.

For the integration of (1) suitable boundary conditions are needed together with initial conditions for all the components that exchange air with BP: Driver's brake valve(s), accelerating chambers, and others, which, in turn, determine some of the source terms of (1). According to this model, each Driver's brake valve (DBV) is modelled as a nozzle placed laterally with respect to BP; each accelerating chamber (AC) is modelled as a lateral nozzle that sets in communication the BP with a small volume. DBV is characterized by an equivalent diameter (D_{DBV}); ACs are characterized by an equivalent diameter (D_{AC}) and by a volume (V_{AC}). All these parameters have to be identified by comparing numerical and experimental results. However, as demonstrated in [14], once a specific parameter of a device (DBV, or other) is identified by means of experimental data, it characterizes that device even if it is employed in a different test. This is one of the main reasons of the application of above model in TrainDy software [15].

2.1. New Pneumatic Solver Scheme

Equations (1) are a set of partial differential equations that have to be solved numerically. In [15] it is mentioned that they can be solved by means of a third-order Taylor expansion of ρ, u, and q. In this paper, a different solver scheme is used: this solver scheme is a classical scheme for fluid-dynamics problems and it is proved to be more efficient and, in some circumstances, more accurate of the third-order Taylor expansion. As in Taylor expansion, space domain has been discretized using a constant mesh of $\Delta x = 1\,m$ and time numerical step of integration is changed dynamically during the computation, considering the time evolution of air density and speed.

Used scheme consists in solving equations like:

$$\frac{dx}{dt} = f\left[x(t), t\right] = y_0 \tag{2}$$

New value is computed as:

$$x(t+\Delta t) = x(t) + a y_0 \Delta t + c y_2 \Delta t \tag{3}$$

Being:

$$\begin{aligned} y_2 &= f\left[x(t) + \Delta t\left(a y_0 + B y_1\right), t + \Delta t\left(a + B\right)\right] \\ y_1 &= f\left[x(t) + A y_0 \Delta t, t + A\Delta t\right] \\ a = \frac{1}{4} \quad c &= \frac{3}{4} \quad A = \frac{8}{15} \quad B = \frac{5}{12} \end{aligned} \tag{4}$$

Of course, $f(x,t)$ is a vector function that lets the computation of $\frac{\partial \rho}{\partial t}$, $\frac{\partial u}{\partial t}$ and $\frac{\partial q}{\partial t}$ according to (1). This numerical method has been proved to have an accuracy of third order.

As mentioned before, time step is not constant but it changes during numerical integration. Naming δ_0 the maximum allowed relative difference of air density from one numerical step to the other and it being computed as $\Delta\rho_{rel} = \max\left[\left|\frac{\rho(t+\Delta t) - \rho(t)}{\rho(t)}\right|\right]$, it is computed the new time step, according to the value of air density variation, as:

$$\Delta t_\rho = \Delta t \sqrt[3]{\frac{\delta_0}{\Delta\rho_{rel}}} \tag{5}$$

δ_0 is fixed according to accuracy and efficiency considerations (it is used 10^{-2}); another time step is computed according to the maximum air speed, as:

$$\Delta t_u = \delta_1 \frac{\Delta x}{\max\left(|u|\right)} \tag{6}$$

Where it is assumed to be $\delta_1 = 0.05$. The minimum of previous time steps is the computed new time step.

3. AUTOMATIC IDENTIFICATION MODEL

As previously described, the pneumatic model is characterized by parameters that need to be calibrated to maximize the agreement between model prediction and experimentally-measured responses. This kind of effort is generally necessary whenever numerical simulations are involved to solve engineering problems. In fact, due to inevitably approximate nature of computer simulations in representing reality, even when input parameters are known, a certain level of tuning is needed as well. Therefore, the success of the application of any numerical model is strongly affected on how well the model is calibrated. In general, manual procedure to achieve the optimal parameters calibration are clearly not the most effective for different reasons i) past knowledge and experience with the model to adjust are necessary ii) trial and error approaches are subjective and laborious iii) calibration becomes progressively more difficult and hence time-consuming as the number of the model parameters increases.

To overcome these issues, two strategies are usually employed: direct or surrogate model-based optimizations.

The main difference among the two is that in the latter approach the output of the computer code is evaluated through surrogate models previously constructed based on the responses of a limited number of chosen data points. It means that the optimization algorithm searches a new design through the surrogate models instead of running a new simulation. In [22] for example, parameters calibration of a material model used in FEA, was developed through this latter approach. The design prediction obtained was much more efficient than the one founded with the computer code because the computational cost associated with the search based on the surrogate models was negligible. In general, using the direct or the model-based approach means shifting the cost-time for the whole optimization procedure from the computational time required by the computer code to evaluate the response to the time needed to build a predictive surrogate model. Evaluating a priori such trade-off for a novel application is not predictable so we made our choice aiming at automating as much as possible the entire procedure. For this reason, we implemented a direct optimization avoiding all the surrogate models related procedure, that require user interventions such as post model checking and ad-hoc Design of Experiments (DoE) building [23].

3.1. Optimization framework

An optimization-based calibration is developed in which the fidelity to measurements is treated as the sole objective and the model parameter values are sought to maximize the correlation between model prediction and experimental data. In particular, we consider the pneumatic model parameters described in section 2 (D_{DBV}, D_{AC}, V_{AC}, K_{conc}, P_{ini}), as input variables, and the error (Err), as the function that have to be minimized. Thus, the minimization problem can be written as:

$$\min\left\{\sqrt{\frac{\sum_i\left[P^E\left(T_i^E\right)-P^N\left(T_i^E\right)\right]^2}{N^E}}\right\} \tag{7}$$

where the objective function is the Euclidean norm in which $P^E(T_i^E)$ are the measured air pressures in BP at time points T_i^E, P^Ntheir numerical counterparts evaluated at the same time points and N^E the number of experimental points.

Table 1 reports the initial values of the 5 input parameters with their upper and lower bound chosen in accordance with the UIC braking component.

Table 1 Parameter's name, its initial value and bounds

Input name	Value	Lower Bound	Upper bound
Diameter of DBV [mm]	18	12	24
Diameter of AC [mm]	5.5	2	9
Volume of AC [l]	1	0.5	1.5
Concentrated pressure loss factor (at hose couplings) [-]	2.75	1.5	4
Initial pressure [bar]	4.85	4.7	5

To solve such minimization problem, several optimization techniques are available in literature [24-26]. For example, deterministic algorithms are most often used if a clear relation between the solution candidate and its fitness exists and the dimensionality of the search space is not very high. Otherwise, the solution research could result in exhaustive enumeration of the search space, which is not feasible even for relatively small problems. On the other hand, Genetic Algorithms (GA) are stochastic, non-linear optimization routines whom heuristic is based on theories of biological evolution [27], generally used to search the global optimum. However, GAs based optimizations are usually time-consuming since the time taken for convergence strongly depends on the population size and the number of generations. Moreover, GAs can easily get stuck on local minima due to the chosen starting population.

To exploit the benefit of such approaches, we use a hybrid algorithm that is a combination of a steady-state (GA) with a Sequential Quadratic Programming (SQP) [26] optimizer. In recent years, in fact, combination of components from different algorithms is one of the most successful trends in optimization. These approaches use some combination of deterministic and randomness or combines one algorithm with another to obtain better performing systems that exploit advantages of the individual pure strategies [28]. Such approaches are commonly referred to as hybrid metaheuristics.

The basic idea is that at the start of the search, GA tries to capture a global picture of the search space, problem-dependent operations are iteratively applied to derive diverse new solutions successively focusing the search on promising regions of the search space. Then SQP local search method is used due to its capability of quickly finding better solutions near given starting solutions. In particular, since SQP is a gradient-based algorithm, derivatives must be approximated. Although the most common and perhaps one of the more precise approximation technique is finite differences, it requires the evaluation of one extra design for each input variable in order to build the complete gradients for a single configuration. Moreover, since these extra points must be very near to their reference one and must lie in strictly defined positions, the possibility of reusing already available information is extremely low and unpredictable. For these reasons, we use Radial Basis Function (RBF) regression scheme [29] to end up with a set of weights assigned to the kernel function that can be derived to compute the required gradients.

The RBF interpolant approximating function have the form:

$$\hat{f}(x) = \sum_{j=1}^{I} c_j \, \phi\left(\frac{\|x - x_j\|}{\delta}\right) \quad (8)$$

where δ is a suitable scaling parameter, $\|\cdot\|$ is the standard Euclidean distance and $\phi(\cdot)$ is the radial or kernel function. In this work we used the Hardy's MultiQuadrics:

$$\phi(r) = \sqrt{r^2 + c^2} \quad (9)$$

where c is a scalar parameter that will be fixed during the training together with δ in order to maximize the precision of the metamodel. The whole process can be logically decomposed as follows:

1) Creation of the parent population from an initial dataset or performing a tournament selection among the actual population.
2) Recombination: mutation, crossover and SQP operators transform parents into children.
3) Archiving: all the intermediate points generated by SQP are stored.
4) On-the-fly update: if a non-dominated point is created, it becomes immediately part of the parent population. Otherwise it is stored in the children archive.
5) Periodic update: the archives are gathered, and elitism is applied. A new population is built, and the loop is restarted.

Steps 2, 3 and 4 form an inner loop which evolves without waiting the completion of the outer one. As a result, all the available computational resources are continuously and intensively employed, minimizing delays.

4. RESULTS OF IDENTIFICATION

As it is described in [15], TrainDy software, owned by UIC and certified against more than 30 experimental tests, incorporates equations (1) and it is able to compute in-train forces of freight trains, by means of its dynamic module. In order to increase the usability of the software and employing the experimental tests carried out by Railway Undertakings in the past years, a “device library” has been computed, by comparing numerical results and experimental tests. Each device has been characterized by a series of parameters that have been identified manually by comparing experimental measurements and their numerical counterparts. Manual identification has been possible, since each parameter has a characteristic influencing zone, even if it affects the numeric fluid-dynamic results as a whole. Main novelty of this paper is that an automatic routine has been set up to perform this identification of parameters and it considers all parameters at the same time, rather than one or two at time, as in [15]. Figure 2 shows an example of time evolution of air pressure in BP for two tests: (a) comes from Trenitalia tests and (b) from DB AG tests. In both cases, train length is around 500 m, but the developed automatic routine can handle any train length or mass. Figure 2 shows experimental measurements with solid lines and numerical counterparts by dashed lines.

Table 2 reports the values of identified parameters under the column labelled as “NEW”. Values reported under the column labelled as “OLD” refer to the manually identified parameters.

Table 2 Parameters, along with error, for the two tests.

Input name	**Trenitalia**		**DB AG**	
	Old	New	Old	New
Diameter of DBV [mm]	16	12	16	14.7
Diameter of AC [mm]	4	8.05	3	2.72
Volume of AC [l]	0.80	1.04	0.8	1.08
Concentrated pressure loss factor (at hose couplings) [-]	2.4	1.61	2.4	2.85
Initial pressure [bar]	4.9	4.93	4.95	4.89
Error (Euclidean norm)	0.651	0.207	0.134	0.074

Figure 3 shows an example of time evolution of air pressure in BP for previous test of Figure 2 (b), when manually identified parameters are employed. In spite of the fact that manual identification brings an error in terms of Euclidean norm bigger than the automatically identified parameters (see Table 1), it is characterized by a better agreement in terms of curvature of the curves. Of course, it is possible to automatic identify the parameters also by considering this feature and this will be done in a future work on the subject.

Initial air pressure in BP deserves a last remark: its value is nominally equal to 5 bar but it is experimentally found in the interval [4.8-5.2] bar. Actually, during normal working conditions, some air pressure usually spills out from the brake pipe (at hose coupling) and the compressor, see label (9) in Figure 1, continuously fills the BP. As a result, air is moving within the BP and its pressure is not constant. TrainDy does not model this condition: it considers air pressure equal in all points of BP and initial air speed equal to zero. Not uniformity of air pressure in BP is a clear experimental feature, as Figure 2 (a) shows. Setting an appropriate value to initial starting pressure affects the Euclidean norm reported in Table 1, but has a minor effect on the computation of air pressure in brake cylinders, on the braking forces and, in turn, on in-train forces.

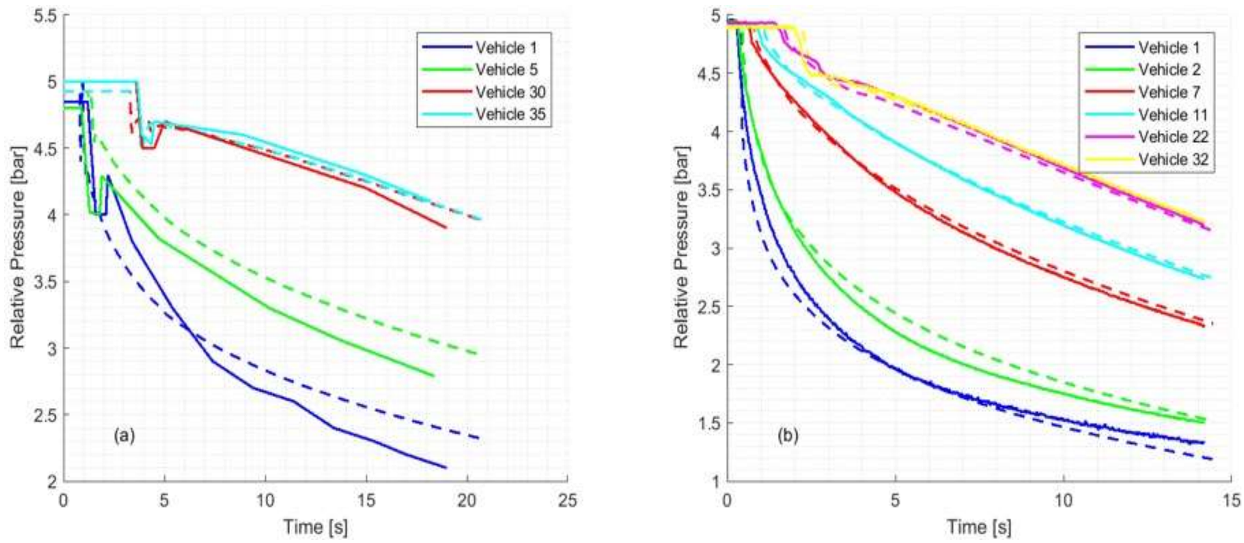

Figure 2 Time evolution of air pressure in BP: (a) Trenitalia Test, (b) DB AG test.

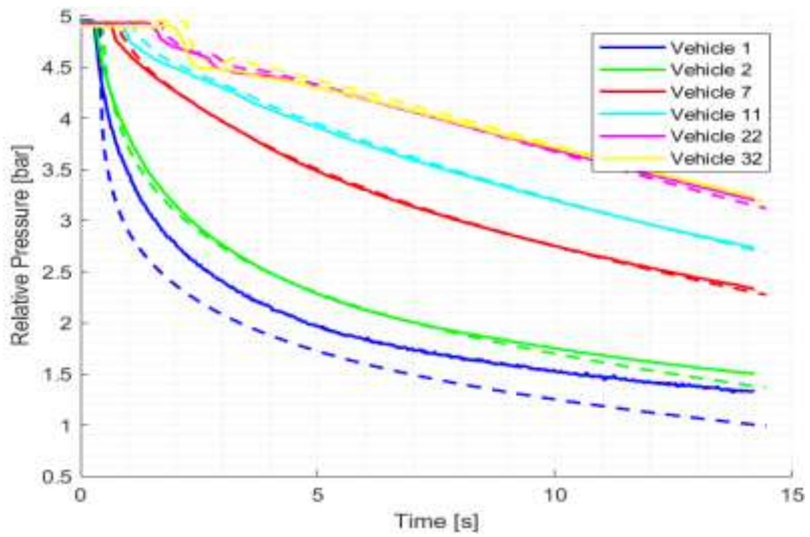

Figure 3 Time evolution of air pressure in BP for DB AG test

5. CONCLUSIONS

Determination of Longitudinal Train Dynamics (LTD) of heavy hauled freight trains is an important task for Railway Undertakings in Europe, especially when they are interested to increase the train length/mass over the usual limits. At this aim, it is crucial determining the air pressure in Brake Pipe (BP) and Brake Cylinders (BC) accurately. Paper illustrates the basic equations of the pneumatic model used in TrainDy software, owned and certified by UIC. Such simplified model is capable to compute air pressure in brake pipe with a high level of accuracy; anyway, it needs some equivalent parameters to be found by comparing numerical data with experimental measurements. This paper shows some results of this identification performed by means of an automatic routine. Main advantage of this routine is that it lets an identification that is more accurate, and it does not require the intervention of an Experienced User. Results show effectiveness of the automatic procedure, even if it can be further improved by adding other parameters to minimize, such as the curvature of air pressure time evolution.

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