Estimation of Rolling Resistance, Tire Temperature and Inflation Pressure of Heavy-duty Vehicle

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***Abstract*—Rolling resistance depends closely on tire temperature and inflation pressure. Effective radius, which affect adhesion coefficient, is influenced by inflation pressure and vehicle velocity. Exploiting this complex relation, this paper proposes a model of this relation and then, a nonlinear observer allowing to estimate the rolling resistance, the tire temperature and the inflation pressure. Using only the measured wheel rotational speed and vehicle velocity, which available from CAN-bus of vehicle, this system does not require any additional physical sensor. This nonlinear observer bases on the sliding-mode observer technique due to its robustness and finite convergence time. The novelty of this approach is the capacity to provide the good estimations of many grandeurs of vehicle tire though the existence of disturbance and variation of uncertain parameters. The challenge obviously still exists with the indistinguishability between rolling resistance and air drag force. The applicability of proposed models and observer is confirmed by the simulation results where the estimation errors are in an acceptable range.**

***Index Terms*—rolling resistance, inflation pressure, tire temperature, effective radius, observer, sliding-mode**

I. INTRODUCTION

Rolling resistance, along with aero dynamics resistance force, is one of the most contributors to fuel consumption problems of vehicle. Passenger car, in general, is light weight and operates at high speed and so, aero resistance is much larger than rolling one. However, in case of heavy-duty vehicle, rolling resistance can account for at least 30 % of total resistance [1]. To reduce fuel consumption, it is necessary to monitor the states of tire-road interaction as well as the rolling resistance during vehicle performance. However, up to now, this task is still a challenge due to the high cost of physical sensors attached on vehicle tires. In this case, virtual (software) sensors are brilliant candidate to solve this problem.

Rolling resistance is a "virtual force", which represents the dissipated energy per distance. This force depends on many factors such as tire material, temperature, pressure, tire-road contact, road pavement, load, and vehicle dynamics [1]. In general, experimental research has shown that rolling resistance coefficient can be modeled as a second order function of vehicle velocity [2], [3]. However, this model is valid only at the conditions where tire temperature is considered as constant (short time).

The influence of tire temperature to Rolling Resistance Coefficient (RRC) is indicated in [3], [4] where RRC is inverse proportional to tire temperature. The reason is that an increase in the tire temperature causes a decrease in the viscosity of tire material and the loss energy. The dynamics of tire temperature was considered as a first-order differential equation [5] while the tire temperature at stationary conditions was considered as a second order function of vehicle velocity [6].

Effective radius which influences directly to the traction force, also has an undetachable link with tire pressure and vehicle velocity. The experimental results of showed that this relation is nonlinear [7]. Tannoury et al. [8] used the high gain observer and second order sliding-mode observer (SMO) for estimating rolling resistance and detecting suddenly decrease of tire pressure had been developed. By comparing mean errors between the real and the estimated values, authors concluded that the sliding-mode observer provides better results than the high gain one thanks to its robustness properties. However, this approach only used the estimated rolling resistance as an indicator for the variations of tire pressure and therefore, it does not allow to estimate the precise value of tire pressure. A multi-physical tire model was developed to consider the temperature and pavement of the road surface [9]. However, the results of the experiments only verified the proposed model while the rolling resistance estimation part was not addressed.

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Second order sliding-mode observer (SMO) for a general form of mechanical systems was presented in [10] which was modified from the super-twisting algorithm and was applied to estimate the wheel speed from the measured wheel rotation angle in [11]. In [12], this observer was used not only for states estimation but also for parameters identification and unknown input reconstruction. In [13], SMO was developed to estimate the lateral forces by using the bicycle model. In [14], the authors tried to estimate separately lateral tire force thanks to the distribution of the vertical loads of each tire. This estimation still exists significant errors between the simulation and the estimated results due to the nonlinearity of lateral forces. In [15], the parameters of heavy vehicle suspension system and vertical tire force were identified and estimated thanks to SMO technique. The results of the experiments confirmed the accuracy of estimated value as well as the finite time convergence properties. Adaptative sliding-mode controller and robust SMO were proposed in [16] to estimate the optimal braking slip ratio and to provide an effective braking adapted to the road condition changes. Not limited in estimation purpose, second order SMO was also used for fault detection in a vehicle cooling system [17]. Besides SMO, extended Kalman filter (EKF) was also widely used to estimate vehicle states and parameters ([18], [19]). In [20], first order SMO and EKF were combined to estimate the vehicle sideslip angle, tire force and to identify the wheel cornering stiffness. Nevertheless, there is no research which exploits the relation among the tire characteristics and the rolling resistance to develop an observer which can replace the real sensors in automotive control system.

In section II, the model of whole system is established which includes the relations among the tire inflation pressure, effective radius, tire temperature and rolling resistance. Based on this model, a sliding-mode observer is designed in the next section after verifying the observability of system. In section IV, simulation results will be presented which allow to evaluate the efficient of this observer, especially in the case with sudden variation of inflation pressure. Finally, some conclusions and perspective of this approach are drawn in the last section.

NOMENCLATURE

SYMBOL	DEFINITION
ω	Wheel rotation speed (rad/s)
v	Longitudinal velocity (m/s)
Γ	Wheel torque (N.m)
M	Vehicle mass (kg)
J	Wheel inertial ((kg.m^2)
F_x	Longitudinal traction force (N)
F_z	Normal vertical force (N)
F_{rr}	Rolling resistance force (N)
C_{rr}	Rolling resistance coefficient
C_f	Wheel shaft viscosity (kg.m^2.s^{-1})
λ	Slip ratio
μ	Adhesion coefficient
R_l	Nominal loaded radius (m)
R	Effective radius (m)
T	Tire temperature (℃)
P	Tire inflation pressure (bar)
P_{nom}	Nominal tire inflation pressure (bar)

II. MODEL OF SYSTEM

A complete model of vehicle is always complicated due to the complex interactions among the sub-systems, especially the interaction between the tires and road surface. This paper focus only on the tire's dynamics where the temperature, pressure and rolling resistance have large contributions. Whole system includes two sub-systems: a quarter-car model and a tire temperature model which is a function of velocity, tire pressure and vertical load. The relation between rolling resistance and tire temperature is considered as a linear equation. In case of typical performance (without a sudden accident), tire inflation pressure seems proportional to tire temperature by ideal gas law. Effective radius, which is influenced by vehicle velocity and inflation pressure, will affects the adhesion coefficient and then, the traction force. All these relations will be integrated in the completed vehicle model.

A. Quarter-Car Model

A typical quarter-car model involves two main parts: longitudinal and vertical part. Vertical part, which presents for suspension system, is normally used to describe the oscillation of vehicle under external excitation. The link between longitudinal and vertical parts is the normal force which is oscillated by the influence of road profile or load transfer. In this paper, this oscillation is considered as an external noise and therefore, the vertical part is eliminated.

Longitudinal part of quarter-car model consists of two motions: translation of vehicle and rotation motion of the wheel. The translational motion is influenced by traction force F_x, rolling resistance force F_{rr} and aero dynamic force F_d. Wheel torque, which is derived from vehicle engine, overcomes resistance torques from traction force and viscosity of wheel shaft to create the rotation of the wheels. These forces are described as follows:

1) Traction force F_x

This force comes from the tire-road interaction and mainly depends on the slip ratio and friction coefficient. The slip ratio of a rolling wheel is defined by:

$$\lambda = 1 - \frac{v}{R\omega} \tag{1}$$

The relation between adhesion coefficient and slip ratio is generally complicated. There are three main models widely used in research on vehicle dynamics: empirical, theoretical and, semi-empirical models. In this paper, to simulate a real vehicle performance as well as to design the observer, we adopted an analytical model in [8]

$$\mu = \frac{2\mu_0\lambda_0\lambda}{\lambda_0^2 + \lambda^2} \tag{2}$$

where λ_0 is the optimal value of slip ratio which creates the maximum value of adhesion coefficient μ_0. The traction force is the product of adhesion coefficient and normal force F_z

$$F_x = F_z\mu(\lambda) \tag{3}$$

2) Rolling resistance force F_{rr}

Similar to traction force, rolling resistance force is also the product of normal force $\mathrm{F_z}$ and rolling resistance coefficient $\mathrm{C_{rr}}$.

$$F_{rr} = F_z C_{rr} \tag{4}$$

Generally, C_{rr} is consider as a second order function of vehicle velocity. In this paper, the effect of tire temperature on C_{rr} is exploited. An increase of tire temperature will decrease the viscosity of tire material and as the results, rolling resistance coefficient will be decreased. Parameter identification from [3], [20], [5] shows that this relation can be approximated by a linear function in the vehicle's velocity operation range. In brief, the proposed model of rolling resistance is described as follows:

$$C_{rr} = \left(\frac{P}{P_{nom}}\right)^{\alpha} \left(C_{rr_{static}} + b_T.(T-25) + c_v.v^2\right) \tag{5}$$

where T is the tire temperature and $P_{nominal}$ is the nominal value of inflation pressure defined by the manufactures. b_T and c_v are the empirical coefficients. $C_{rr_{static}}$ is the static part of rolling resistance and is considered as constant during the performance of vehicle. This value depends on the vertical load, road type, wheel alignment and tire material at 25^0C. The dynamics part includes a first order function of tire temperature and a second order function of vehicle velocity. Tire inflation pressure P has general effect on both part of C_{rr} and is assumed to be driven by T through ideal gas law:

$$P = P_{nom} \frac{T + 273}{T_{initial} + 273} \tag{6}$$

where $T_{initial}$ is the initial value of tire temperature.

3) Aerodynamics force

This resistance comes from the interaction with air flow around vehicle. In general, it is proportional to square of vehicle velocity as follows:

$$F_d = \frac{1}{2} \rho A_d C_d v^2 \tag{7}$$

4) Dynamics of quarter-car model

The translational and rotational motions of wheel are covered by two *equations*

$$\begin{cases} \dot{v} = & \frac{1}{M}(F_x - F_d - F_{rr}) \\ \dot{\omega} = & \frac{1}{J}(\Gamma - F_x R - C_f \omega) \end{cases} \tag{8}$$

B. Tire Temperature Dynamics

In [5], tire temperature dynamics of a vehicle can be expressed by a first order equation

$$\dot{T} = \frac{1}{\tau}(-T + T_{sc}) \tag{9}$$

With time constant τ is a function of vehicle velocity as in (10). According to [4], τ can vary from 30 to 90 minutes depending on type of vehicle.

$$\tau = \tau_\infty - (\tau_0 - \tau_\infty) e^{-\frac{1}{\sigma} v} \tag{10}$$

With σ, τ_0 and τ_∞ are empirical constants and T_{sc} is the tire temperature at stationary conditions depending on the vehicle velocity and vertical load as follows (adapted from [6]):

$$T_{sc} = a v^2 + (b_1 F_z + b_2) v + T_{ambient} \tag{11}$$

With $T_{ambient}$ is the ambient temperature.

C. Effective Radius as Function of Pressure and Velocity

Effective radius is proportional to the vehicle speed and the tire inflation pressure. Although this relation is generally nonlinear, an acceptable linear approximation can be done within a range of ±25% around the nominal value of tire pressure [7]. In this paper, we proposed a model of this relation as follows:

$$\Delta R = a_R.\Delta P + b_R.v \tag{12}$$

where ΔR (%) , ΔP(%) representing for the relative change of effective radius and of tire pressure, respectively, are defined as follows:

$$\Delta R = \frac{R - R_l}{R_l} \times 100; \Delta P = \frac{P - P_{nominal}}{P_{nominal}} \times 100 \tag{13}$$

It is obviously that ΔR also depends on variation of vertical normal force. However, for simplification reasons, it can be supposed that the vehicle works under nominal load and so the influence of normal force is neglected.

III. Observer Design

In this section, the sliding mode observer for vehicle and tire states will be developed. Firstly, a complete model of vehicle will be finalized. Observability of system will be analyzed thanks to numerical evaluation technique. At the end, a first order sliding mode observer will be proposed.

A. Completed Model of System

To monitor the changes of tire inflation pressure, it is necessary to consider this grandeur as a state variable which is driven by an unknown input through an integrator. Combining with (7) and (8), the final model is as follows:

$$\begin{cases} \dot{x}_1 = & \frac{1}{M}\left(F_x(x) - F_d(x_1) - F_{rr}(x)\right) \\ \dot{x}_2 = & \frac{1}{J}\left(u - F_x(x)R - C_f x_2\right) \\ \dot{x}_3 = & \frac{1}{\tau}\left(-x_3 + T_{sc}(x_1)\right) \\ \dot{x}_4 = & \eta \end{cases} \tag{14}$$

With $x = [x_1 \quad x_2 \quad x_3 \quad x_4]^T = [v \quad \omega \quad T \quad P]^T, u = \Gamma$ and η is a bounded unknown input.

B. Analysis of Observability of System

In this system, only the longitudinal velocity of the vehicle and the rotation velocity of the wheels (the states x_1 and x_2) are measured directly by standard sensors on vehicle. The two remain variables should be estimated by an appropriated observer if the observability of system is confirmed. To verify this condition, local observability rank condition test based on Lie derivatives of the outputs of systems will be used.

Local observability rank condition test:

Give a nonlinear system had the form:

$$\begin{cases} \dot{x} = f(x,u) & x \in R^n, u \in R^m \\ y = h(x) & y \in R^p \end{cases} \tag{15}$$

For each input $u^* \in R^m$, define a matrix $Q \in R^{(p \times n) \times 1}$ of output y and its derivatives at state x_0:

$$Q(x_0, u^*) := \begin{pmatrix} h(x) \\ L_f h(x) \\ L_f^2 h(x) \\ \dots \\ L_f^{n-1} h(x) \end{pmatrix} \tag{16}$$

The system (15) satisfies local observability rank condition at x_0 if:

$$Rank\left[\left.\frac{\partial Q(x_0, u^*)}{\partial x}\right|_{x=x_0}\right] = n \tag{17}$$

C. Sliding-Mode Observer

From (14), a first order sliding-mode observer is proposed by reusing the model of system and adding some robust terms as in (18)

$$\begin{cases} \dot{\hat{x}}_1 = \dfrac{1}{M}\left(F_x(\hat{x}) - F_d(\hat{x}_1) - F_{rr}(\hat{x})\right) + L_1 e_1 \\ \dot{\hat{x}}_2 = \dfrac{1}{J}\left(u - F_x(\hat{x})R - C_f \hat{x}_2\right) + L_2 e_2 \\ \dot{\hat{x}}_3 = \dfrac{1}{\tau}\left(-\hat{x}_3 + T_{sc}(\hat{x}_1)\right) + L_3 sign(e_1) \\ \dot{\hat{x}}_4 = L_4 sign(e_2) \end{cases} \tag{18}$$

With $e_1 = x_1 - \hat{x}_1, e_2 = x_2 - \hat{x}_2$ and the observer gains L_1, L_2, L_3, L_4 can be chosen appropriately to make the estimated states converge to the real values. The first two states x_1, x_2 are estimated by the classical Luenberger observer while the last two states are estimated by the first order sliding mode observer.

TABLE I. QUARTER-CAR MODEL'S AND TIRE'S PARAMETERS USED IN SIMULATION

Parameters	Symbol	Unit	Value
Wheel Inertia	J	$kg \cdot m^2$	15
Loaded radius	R_l	m	0.48
Quarter-car mass	M	kg	5200
Max adhesion coefficient	μ_0		0.9
Optimal slip ratio	λ_0		0.25
Frontal area	A_d	m^2	0.425
Drag coefficient	C_d		0.25
Air weight density	ρ	$kg.m^{-3}$	1.205
Viscosity coefficient	C_f	$kg \cdot m^2 \cdot s^{-1}$	0.085
Gravitational acceleration	g	$m \cdot s^{-2}$	9.81

TABLE II. TIRE MODEL'S PARAMETERS USED IN SIMULATION

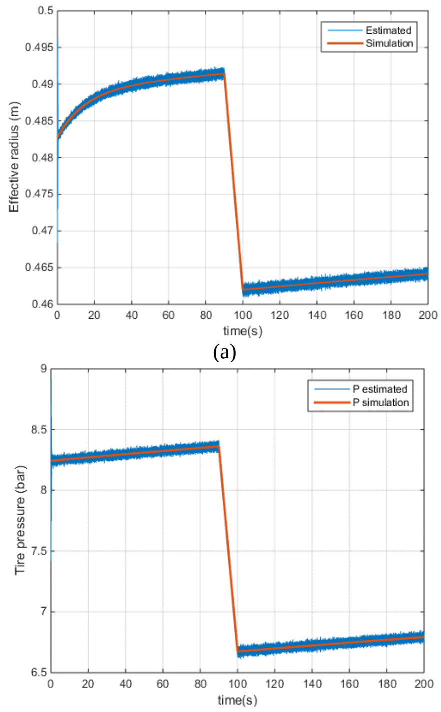
Symbol	Value
a_R	0.3
b_R	0.04
τ_0	3818
τ_∞	864
σ	2.45
$C_{rr_{static}}$	5.66
b_T	-0.01327
c_v	$3.519 \cdot 10^{-5}$
a	-0.0045
b_1	$1.025 \cdot 10^{-5}$
b_2	0.6013

IV. SIMULATION RESULTS

To validate the proposed observer, the numerical simulation is conducted in Matlab/Simulink environment with quarter-car parameters are given as in Table I where selected values of μ_0 and λ_0 are adapted from [8]. Step time of simulation environment is 2.10^{-4} s. The coefficients relating to model of rolling resistance, tire temperature and effective radius is summarized in Table II The values of a_r and b_r are obtained from assumptions: *20% variation in pressure around nominal value creates 6% change in effective radius; 1 km/h variation in longitudinal velocity creates 0.04% change in effective radius.* The parameters of tire temperature dynamics are adapted from [6] while $C_{rr_{static}}$, b_T and c_v are extracted from data in [5] by using curve fitting toolbox in Matlab.

In this first work, parameters of quarter-car model are chosen based on a truck vehicle where rolling resistance plays an important role in total resistance force. However, this model is obviously applicable to wide range type of vehicle, with appropriated modifications of parameters.

A. Simulation Scenario



(a)

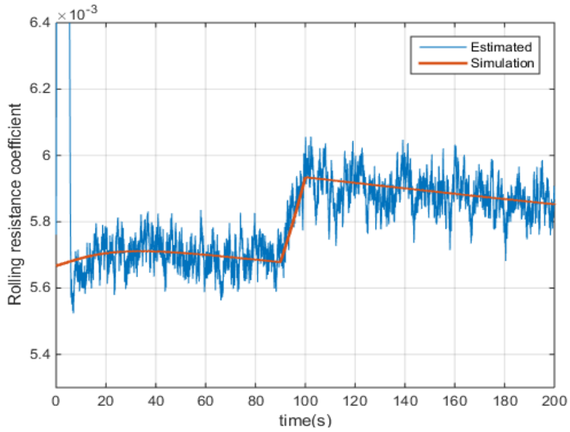
(b)

Figure 1. Simulation results. (a) Estimation of tire effective radius (m) versus time(s). (b) Estimation results of tire inflation pressure (bar) versus time(s)

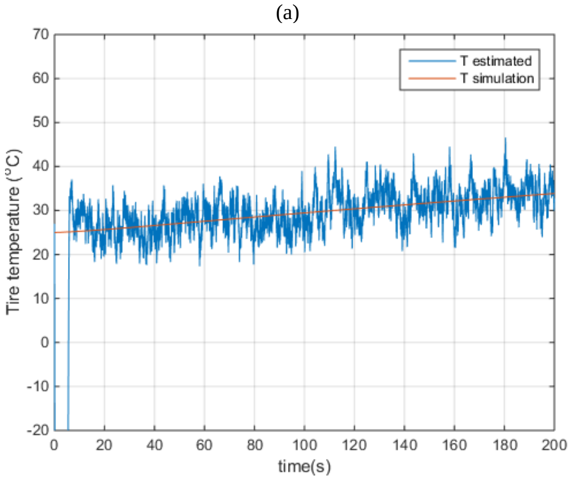
During the simulation with the completed quarter-car model (14), the longitudinal velocity is maintained constant thanks to a simple PID controller. A white noise with a variance 0.5% of measured values is inserted to the measurements of rotational speed and longitudinal velocity. To simulate a sudden variation of inflation pressure, a 20% drop in tire pressure is created from $t_1 = 90s$ to $t_2 = 100s$.

B. Simulation Results

Simulation data is collected to verify the observability of system. The matrix rank test in Section III-B is done showing that this matrix is always full rank (rank = 4) along the working trajectory. Therefore, the observability of system is assured. The observer gains are chosen: $L_1 = 0.1; L_2 = 200; L_3 = 10^5; L_4 = 100$. The initial values of vehicle system and of sliding mode observer are $[v(0) \quad \omega(0) \quad T(0) \quad P(0)] = [14 \quad 28 \quad 25 \quad 8.2]$ and $[\hat{v}(0) \quad \hat{\omega}(0) \quad \hat{T}(0) \quad \hat{P}(0)] = [15 \quad 30 \quad 27 \quad 7.4]$, respectively.



(a)



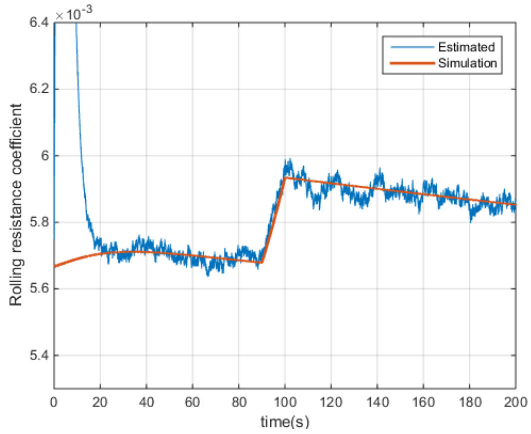
(b)

Figure 2. Simulation results with $L_1 = 0.1; L_3 = 10^5$. (a) Estimation of rolling resistance coefficient versus time(s). (b) Estimation results of tire temperature (^{0}C) versus time(s)

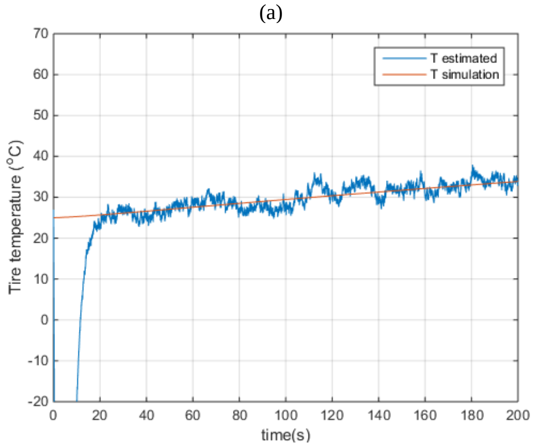
Fig. 1 shows that the proposed observer well estimate the tire pressure and effective radius. The convergence time is only about 0.5s. The oscillation of observed pressure and effective radius are acceptable because they are enough small in comparison to real values with mean errors are only 0.17% and 0.04% for tire pressure and effective radius, respectively (formulas for calculation of mean errors are presented in section IV-C). However, this is not the case of rolling resistance and tire temperature.

As can be seen in Fig. 2, convergence time of estimations of rolling resistance and tire temperature is about 8s. Estimated values are strongly noisy with mean errors are about 9.9% and 0.68% for tire temperature and RRC, respectively. The reason for large error of estimated tire temperature is that RRC is not sensitive to the change of tire temperature. As the results, a small estimation error of RRC leads to a large error of estimated temperature.

To reduce this error, a change of observer gains will be made with a reducing the gain of tire temperature dynamics equation ($L_3 = 10^4$). Fig. 3 demonstrates the results of this modification. The estimation errors are improved significantly with only 3.4% for tire temperature and 0.24% for RRC. However, time of convergence is also increased to about 18s. Therefore, in practice where the measurement noises always exist, it is necessary to make a tradeoff between the convergence time and estimation errors.



(a)



(b)

Figure 3. Simulation results with $L_1 = 0.1; L_3 = 10^4$. (a) Estimation of rolling resistance coefficient versus time(s). (b) Estimation results of tire temperature (^{0}C) versus time(s)

It should be noted that the proposed observer also works well in case of a sudden drop of tire pressure although it has no information about tire pressure dynamics. This advantage allows to monitor tire pressure without physical sensors in real applications. The estimated values of RRC, tire pressure and effective radius are always kept track of the real ones while the tire temperature maintains its trends. This result reflects an actual situation where three first grandeurs will response rapidly to unexpected change of inflation pressure. In contrast, tire temperature's response time is much larger due to the nature of its dynamics.

C. Influence of Uncertain Parameters

In this section, one assumes that there are some differences in model of observer and model of system. This assumption is reasonable because the parameters uncertain always exists in a real system. Suppose that the parameters used in section IV-A are the standard ones, some typical cases of parametric variation can be proposed as follows:

Case 0: Standard case

Case 1: Noise variance = 5% measured value

Case 2: Vehicle mass = 80% standard value

Case 3: $a_R = 0.24; b_R = 0.048$

Case 4: $\tau_0 = 2000; \tau_\infty = 1000;$

Case 5: $\lambda_0 = 0.2; \mu_0 = 0.8;$

In each case, the estimation errors will be evaluated by calculating the relative mean estimation errors $\bar{e}_T, \bar{e}_P, \bar{e}_{rr}$ and $\bar{e}_R$ as follows:

$$\begin{aligned}\bar{e}_T &= \frac{1}{N}\sum_{i=1}^{N}\left|\frac{T(t_i)-\hat{T}(t_i)}{T(t_i)}\right| \\ \bar{e}_P &= \frac{1}{N}\sum_{i=1}^{N}\left|\frac{P(t_i)-\hat{P}(t_i)}{P(t_i)}\right| \\ \bar{e}_{rr} &= \frac{1}{N}\sum_{i=1}^{N}\left|\frac{C_{rr}(t_i)-\hat{C}_{rr}(t_i)}{C_{rr}(t_i)}\right| \\ \bar{e}_R &= \frac{1}{N}\sum_{i=1}^{N}\left|\frac{R(t_i)-\hat{R}(t_i)}{R(t_i)}\right|\end{aligned} \tag{19}$$

With t_i is counted from instant when estimated values start converging to real ones to 200s and N is the number of samples in this period. Observer gains are fixed to $L_1 = 0.1; L_2 = 200; L_3 = 10^4; L_4 = 100.$

TABLE III. SIMULATION ERRORS OF ESTIMATED GRANDEURS

Case	$\bar{e}_T(\%)$	$\bar{e}_P(\%)$	$\bar{e}_{rr}(\%)$	$\bar{e}_R(\%)$
0	3.4	0.13	0.25	0.035
1	5.06	0.22	0.37	0.06
2	12	0.12	0.86	0.03
3	4.9	1.08	0.29	0.03
4	3.53	0.12	0.25	0.03
5	4.15	0.14	0.29	0.04

Estimation errors in six cases are summarized in Table III. In most of cases, the robustness of this observer is assured with the estimation errors are smaller than 5%, except for case 2 (12%) where the vehicle mass is varied. This can be explained by the proportional properties between the vehicle mass and the rolling resistance. An error in vehicle mass value corresponds to a variation in RRC which leads to large error in estimation of tire temperature. This result suggests that it is necessary to well estimate the vehicle mass before carrying out any estimation of RRC and tire temperature.

V. CONCLUSIONS

A first order sliding-mode observer is proposed to estimate the tire temperature, pressure, effective radius and rolling resistance of a heavy-duty vehicle. This observer provide good estimation results through simulation results can be used to detect the unexpected change of inflation pressure. This observer uses only standard signal from CAN-bus of vehicle and therefore, it is a promising solution to monitor a set of tire parameters without expensive real sensors. In the future, the experiments with various kind of vehicles are necessary to validate the quality of this method. In addition, looking for a solution to improve the precision of estimated tire temperature and rolling resistance in case present of noise is also an open problem. It is also clear that this observer should be tested online when vehicle is operating in real-life driving conditions.

CONFLICT OF INTEREST

The authors declare no conflict of interest.

AUTHOR CONTRIBUTIONS

All authors contributed to the design and implementation of the research, to the analysis of the results. V.T. NGUYEN and V.D. NGUYEN wrote the manuscript in consultation with M. BOUTELDJA.

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