Chapter 22
Agile Tyre Mobility: Observation and Control in Severe Terrain Environments

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Abstract This research study develops fundamentals for a new ground vehicle technology to radically improve and protect off-road vehicle mobility by providing agile (fast, exact and pre-emptive) responses and advanced mobility controls in severe terrain conditions.

The current framework of terrain vehicle mobility that estimates a vehicle capability "to go through" or "not to go through" the given terrain conditions cannot provide an analytical basis for novel system design solutions. Indeed, modern traction control and other mobility related electronic control systems possess control response time within the range of 100–120 milliseconds and greater. With this response time, the actual control occurs after the vehicle has reached a critical motion situation, e.g., a wheel(s) is/are spinning and the vehicle is already losing its mobility. In this study, the developed methods allowed for estimating tyre mobility and controlling tyre motion before the tyre starts spinning. As shown in the conducted analysis, the response time, which occurs within the longitudinal tyre relaxation time constant of 40–60 ms, is sufficient for a tyre to avoid spinning and to maintain its required mobility.

Most common traditional approaches to observation of data supplied by virtual sensors were simulated and improved by means of machine learning algorithms. Computational simulations of an one-wheel-locomotion module driven by an electric driveline system demonstrated a sufficient performance of the proposed observation method to estimate mobility margins of the module in real time.

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A hybrid intelligent control algorithm was designed, in which reinforcement learning was used to fine-tune the parameters of a fuzzy logic controller. A new wheel mobility index was utilized as a cost function to guarantee a designed behavior of the locomotion module. A fuzzy corrector was additionally designed to take into account both the dynamic state of the system and the dynamics of the tyre-terrain interaction. The fuzzy corrector supports upper level controls of autonomous vehicle dynamics by decreasing tyre slippage on severe terrains.

Computer simulations testified both stability of the controller (due to utilization of fuzzy logic polynomial control) and its desired performance (due to application of reinforcement learning). The fine-tuned controller requires minimal online computations.

This paper provides an extended summary of the above-listed research studies. Further details can be found in publications referenced in the paper.

Keywords Agile terrain mobility · Real-time observer and controller

22.1 Introduction

Further improvements of terrain mobility of vehicles can be achieved by reducing the response time of the modern vehicle electronic systems, including Traction Control and Torque Vectoring systems. Indeed, by using real-time controls being capable to operate within a short period while tyre is still developing its slippage would enhance vehicle mobility.

When developing a controller, a cost-function that provides the desired system behavior has to be utilized. Such function based on the wheel mobility index was introduced in Vantsevich et al. [1]. This index was further used to synthesize an intelligent control of the open-link locomotion module Vantsevich et al. [2, 6]. Two approaches were used for this purpose: one approach utilized reinforcement learning and the other one used hybrid intelligent control, in which reinforcement learning was used to fine-tune the parameters of fuzzy logic controller. The second approach testified both stability of the obtained controller (due to utilization of fuzzy logic polynomial control) and the desired performance (due to application of reinforcement learning). The utilization of the fine-tuned fuzzy controller for real-time agile control became possible due to minor online computations required by this type of controller. The designed intelligent control significantly decreased the response time in various severe terrain conditions. The controller demonstrated its robustness and stability.

Additionally, based on a comprehensive analysis of both traditional and modern control methods was done in Vantsevich et al. [3], a fuzzy corrector was introduced in Vantsevich et al. [4]. The fuzzy corrector main goal was to support either a driver or to contribute the system level control of an autonomous vehicle to decrease tyre slippage.

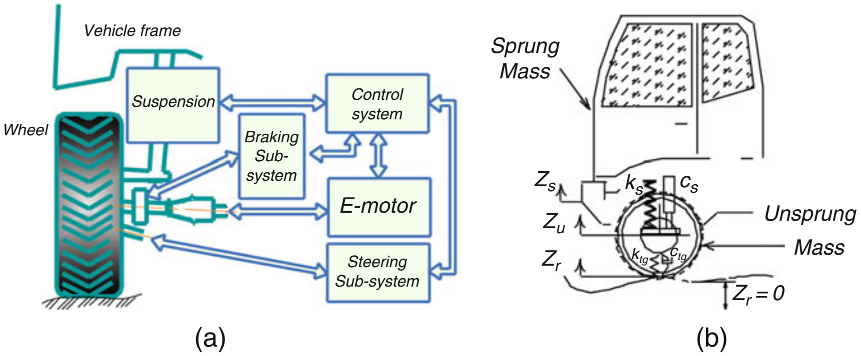

Fig. 22.1 Diagram of the open-link locomotion module: (**a**) rotational subsystem (**b**) vertical subsystem

22.2 Open-Link Locomotion Module Model

The open-link locomotion module model is a mathematical representation of a vehicle module (see Fig. 22.1a) that combines a wheel driven by an electric motor, a gear set, a brake sub-system, steering, and suspension [10, 11]. The model is represented by Eqs. (22.1) and (22.2), where Eq. (22.1) describes the rotational dynamics and Eq. (22.2) corresponds to the normal dynamics (see Fig. 22.1b).

$$\begin{cases} \frac{di_m}{dt} = \frac{1}{L_a}\left(U - R_a i_m - e\right), \\ U = \frac{k_{bat} u}{u_{\max}}, \\ J_{eq} = J_m + \sum_{l=1}^{k} \frac{J_l}{i_l^2}, \\ J_{eq}\dot{\omega}_m = T_m - k_{eq}\left(\varphi_m - i\varphi_w\right) - c_{eq}\left(\omega_m - i\omega_w\right) - T_{fm}, \\ T_{fm}\left(\omega_m\right) = \alpha_{0m}\operatorname{sign}\left(\omega_m\right) + \alpha_{1m}\exp\left(-\alpha_{2m}\left|\omega_m\right|\right)\operatorname{sign}\left(\omega_m\right), \\ i = \frac{\omega_m}{\omega_w}, \\ T_m = k_t i_m, \\ T_s = k_{eq}\left(\varphi_m - i\varphi_w\right) + c_{eq}\left(\omega_m - i\omega_w\right), \\ \varphi_m = \varphi_1 - \varphi_2 \\ \varphi_w = \varphi_3 - \varphi_4, \\ J_w\dot{\omega}_w = ik_{eq}\left(\varphi_m - i\varphi_w\right) + ic_{eq}\left(\omega_m - i\omega_w\right) - T_{wl} - T_{fw}, \\ T_{fw}\left(\omega_w\right) = \alpha_{0w}\operatorname{sign}\left(\omega_w\right) + \alpha_{1w}\exp\left(-\alpha_{2w}\left|\omega_w\right|\right)\operatorname{sign}\left(\omega_w\right). \end{cases} \tag{22.1}$$

here, J_{eq} is a rotational inertia of the equivalent mass; J_m and J_l are the rotational inertias of the rotor and an l-gear of the gear set, $l = 1, k$ correspondingly (see Fig. 22.2a); i_l is the velocity ratio between the l-gear of the gear set and the rotor, i is the total velocity ratio of the gear set between the motor and the wheel; ω_m, and ω_w are the angular velocities of the rotor and the wheel; k_{eq} is the equivalent torsional damping; c_{eq} is the stiffness shafts; T_s is the internal elastic-damping torque in the

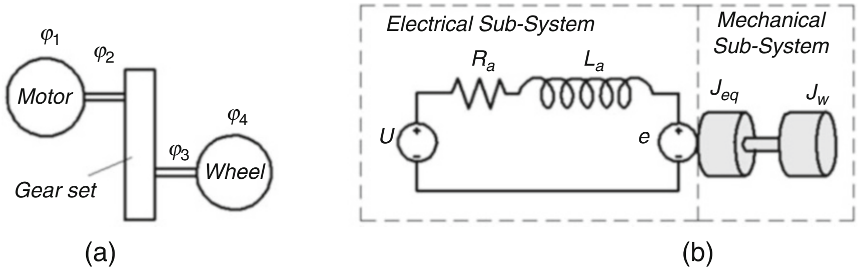

Fig. 22.2 Kinematic (**a**) and mechatronic (**b**) diagram of the drive sub-system

gear set; φ_m and $\varphi_w$are the instant revolution angles of the e-motor shaft and the wheel shaft; R_a is the armature electric resistance; L_a is the armature inductance; U in Fig. 22.2b stands for the armature voltage; e is the back electromotive force, which is the product of the back EMF constant, k_{emf}, and the angular velocity of the e-motor, ω_{m}; T_m is e-motor torque; i_m is electric current; k_t is the e-motor constant; u is a control voltage; k_{bat} is the maximum voltage output of the *Pulse Width Modulation* battery; u_{max} is the maximum control voltage; T_{wl} is the load torque caused by terrain; T_{fm} (ω_m) is the mechanical friction torque; α_{0m} is a constant that represents the Coulomb friction torque; α_{1m} is a constant that represents the difference between the Coulomb friction torque and the static friction torque; α_{2m} is a time constant; T_{fw} is the mechanical friction torque in the wheel bearings; α_{0w} is the Coulomb friction; α_{1w} is the static friction torque; α_{2w} is a time constant

$$\begin{cases} R_z = \mathrm{W}_w \cos\theta_n + k_{tg}\left(z_r - z_u\right) + c_{tg}\left(\dot{z}_r - \dot{z}_u\right) \\ m_s \ddot{z}_s = k_s\left(z_u - z_s\right) + c_s\left(\dot{z}_u - \dot{z}_s\right), \\ m_u \ddot{z}_u = k_{tg}\left(z_r - z_u\right) + c_{tg}\left(\dot{z}_r - \dot{z}_u\right) - k_s\left(z_u - z_s\right) - c_s\left(\dot{z}_u - \dot{z}_s\right). \end{cases} \tag{22.2}$$

where, R_z is the dynamic normal reaction; θ_n is the slope of the surface of motion; W_w is the static wheel load caused by the sprung mass and the unsprung mass; k_{tg} is the tire-soil normal stiffness; c_{tg} is the tire-soil damping factor; z_s and z_u are the displacements of the sprung and unsprung masses, m_s and m_u; z_r is the height of the terrain profile; k_s and c_s are the reduced stiffness and damping of the suspension.

In Eq. (22.1), φ_1, φ_2, φ_3, φ_4 represent instant revolution angles of the ends of the shafts between motor and gear set, wheel and gear set (Fig. 22.2a). Due to the elastic properties of material of the shafts and gears, these angles are different.

22.3 Agile Control Response Time

As pointed out in [5], the agility of the tyre control means the ability of a control algorithm to respond within a predefined time, which is small enough to implement the control before the tyre develop an extensive slippage. The aim of the small response time is to establish a new traction force between the wheel and the terrain that would eliminate the extensive slippage. The electric motor torque cannot be instantly converted in the traction force due to the longitudinal deflections of tyre and soil, which are referred as the longitudinal relaxation time constant:

$$\tau_{rl}(t)\frac{dF_x(t)}{dt} + F_x(t) = F_{ssx} \tag{22.3}$$

here, $\tau_{rl}(t)$ is the longitudinal tire relaxation time constant, $F_x(t)$ is the dynamic circumferential wheel force, F_{ssx} is the steady-state circumferential wheel force.

As shown in [6], the longitudinal relaxation time constant is a measure of the tyre reaction to variations of terrain and operational conditions. A control algorithm that is to be deployed on the vehicle has to function in response to the conditions within the time interval that is the longitudinal relaxation time constant. Taking into account considerations research outcomes of [6], the response time of the control has to be within 40–60 ms. This will allow for providing agile real-time control of tyre mobility.

22.4 Virtual Sensor Design

The design of virtual sensors means the usage of virtual observers that can provide necessary and sufficient information on the system states using a few physical sensors, i.e., the observers serve as virtual sensors. A detailed overview of existing observers can be found in [7]. Figure 22.3 and Fig. 22.4 illustrate applications of some algorithms to observe the wheel normal reaction and the elastic damping torque of the module. An analysis of these simulation results allowed for concluding on utilizing the observers for in real-time applications (see [8]).

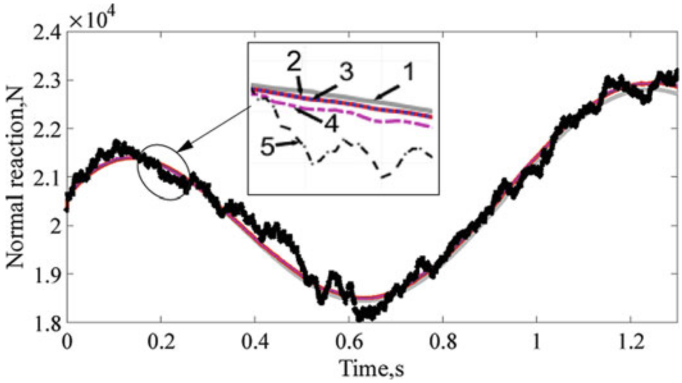

Fig. 22.3 Estimation of the wheel normal reaction by Extended Kalman Filter (EKF), Unscented Kalman filter (UKF), Particle filter (PF), Luenberger observer (LO)

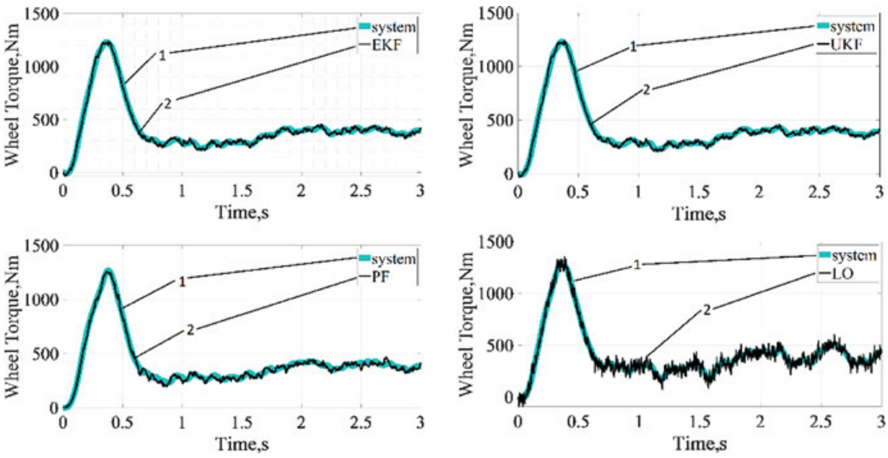

Fig. 22.4 The estimation of the elastic-damping torque by EKF, UKF, PF, and LO: black lines are the computed states; cyan lines are the estimated states

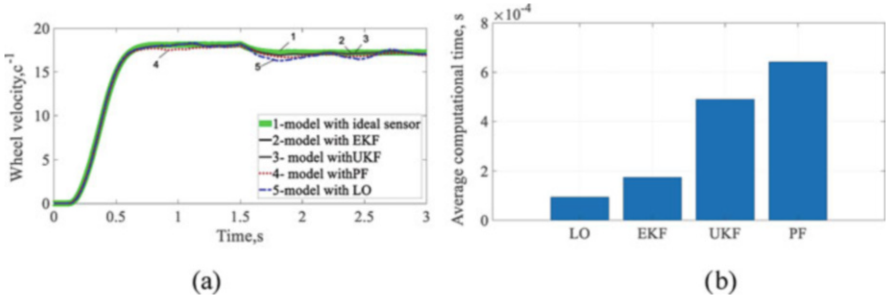

Fig. 22.5 (**a**) The dynamics of the system (1)–(2) with ideal sensors and the system with EKF, UKF, PF and LO; (**b**) Average time of observation using four algorithms

The obtained results show that it is possible to design an observer that is accurate enough, robust, and convergent even influences to noise. Figure 22.5a demonstrates the values of the wheel velocity calculated with the observer subjected to sensor noise and with ideal sensors (i.e. without any noise). Moreover, each designed observer can work alongside controller in real-time. As seen from Fig. 22.5b, the maximum time of response time is 0.8 ms which is much less than 40–60 milliseconds of the tyre relaxation time constant.

22.5 Fuzzy Corrector

A fuzzy logic controller that modifies an incorrect control input that may come either from a driver or from an autonomous control system of the electric motor. The incorrect input can be smoothened and a new, modified input can

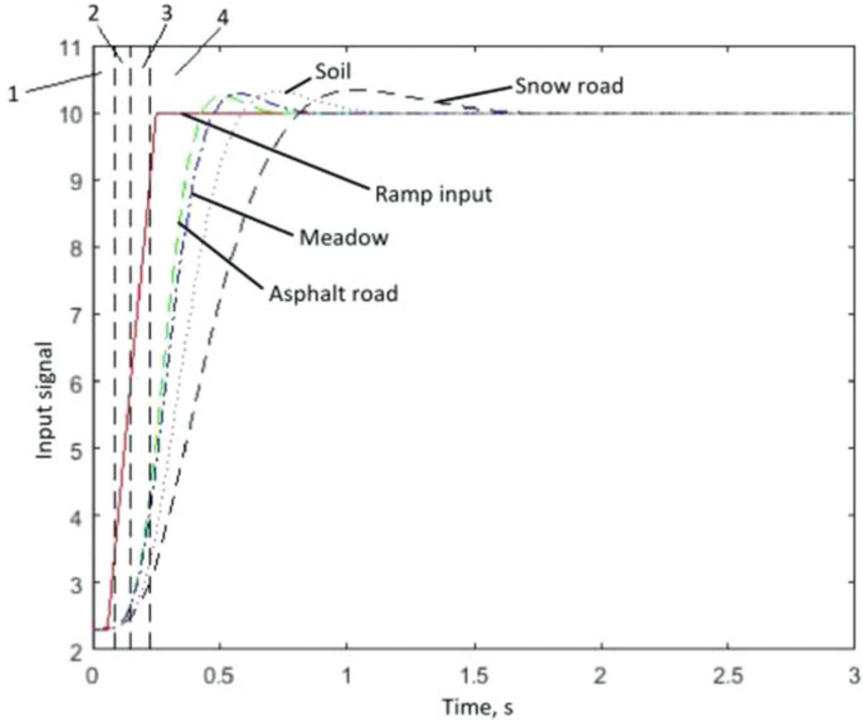

Fig. 22.6 Incorrect input signal illustrated by the ramp input and smoothened input signals on different terrains

be introduced. Details on this technical approach are explained in Vantsevich et al. [4].

Assuming an incorrect input signal varies from 0 to $u_{\max}$, the maximal value that may be generated by the Pulse Width Modulation signal is also $u_{\max}$. Figure 22.6 illustrates the input signal that is considered as an incorrect. This signal is further smoothened by the proposed fuzzy corrector. The smoothened input with a longer response time can reduce extra tyre slippage. The subdomains, labeled as 1, 2, 3 and 4 correspond to different levels of activation of the fuzzy logic rules from the rule base. The corrector acts swiftly and in a short time frame, however its performance has significant influence on the behavior of the locomotion module.

As an example of computational results, Fig. 22.7 demonstrates characteri-stics of the module for the ramp input and the smoothed input on a snow road.

The fuzzy corrector reduces the tyre slippage and provides the desired rotational velocity of the wheel at the set point. This was obtained by smoother changes of the electric current, the torque, and the rotational velocity in area 1. An increased rate of the controller's signal in the middle of the wheel acceleration process (areas 2 and 3) allows for keeping up with a response time of the locomotion module; a steady

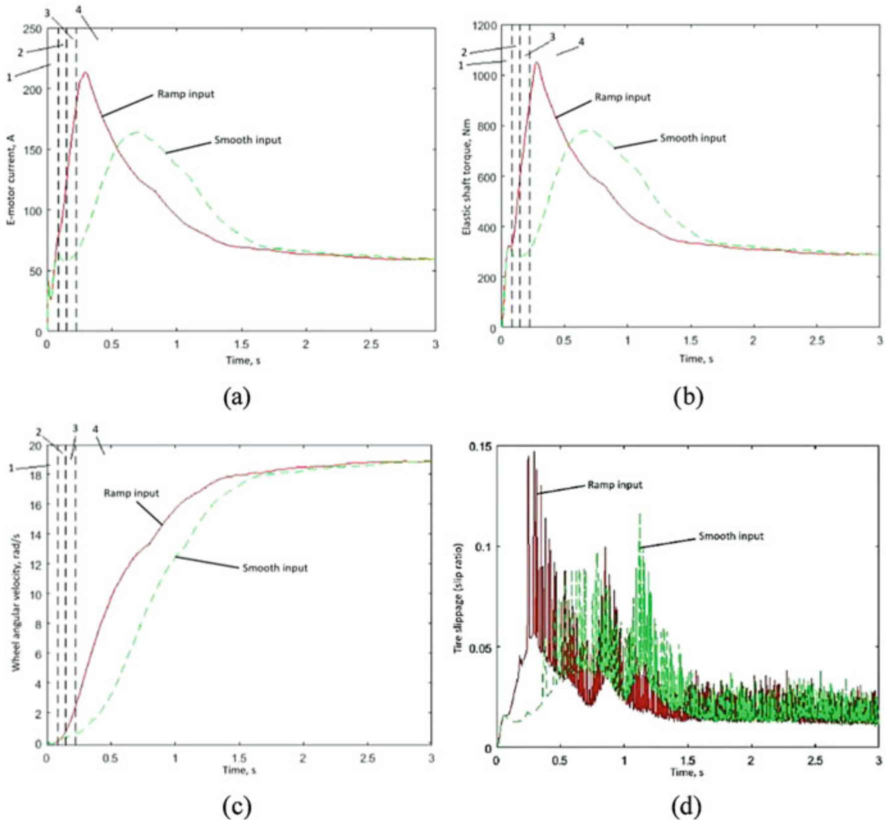

Fig. 22.7 Comparison of system characteristics on a snow road: (**a**) comparison of motor current values; (**b**) comparison of motor shaft torque values; (**c**) comparison of wheel angular velocities; (**d**) comparison of tyre slippages

state phase is achieved after 1.5 sec. Area 4 shows the inputs (i.e., the rotational velocity) smoothened to the set point.

22.6 Fuzzy Controller

As shown in [9, 12], a utilization of an unstable subsystem may significantly increase efficiency of a controller. The unstable controller acts only in the region of the large errors, which means that a system that is close to the steady state will be stable, and there is a transient region where both stable and unstable subsystems are active.

Figure 22.8a represents the hodograph of the system with unstable subsystem. Traditionally, the pass of the roots is along the convex curve. However, other trajec-

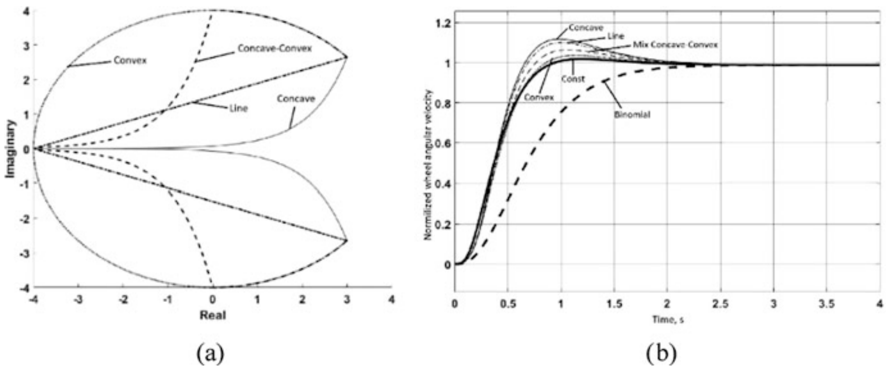

Fig. 22.8 (**a**) The hodograph of the roots in the case of a system with a fuzzy controller; (**b**) Trajectories of the output signal of the system in the case of shown hodographs

tories can be possibly utilized: concave, linear, etc. Moreover, these trajectories can be obtained by calculating the weight function of the fuzzy rules that would allow for obtaining the desired trajectories.

The results of the simulation are presented on Fig. 22.8b. As one can see, the transients of the system with non-standard trajectories are better than in the case of convex trajectory. However, computational efforts are significant. Therefore, to ensure real-time computation, a convex trajectory of the root has to be used.

22.7 Fuzzy Reinforcement Learning Controller

As shown in the previous sections of this paper, the utilization of the fuzzy controller and the fuzzy corrector adds significant improvements to the behavior of the system. However, these controller and corrector require a manual tuning. In this study, reinforcement learning was applied to calculate the output signal of the controller depending in the state of the system and disturbances (including terrain conditions). Hence, reinforcement learning was applied to fine-tune the parameters of the fuzzy membership function. This approach allowed for obtaining an optimal behavior of the control system and, what is even more important, for achieving stability of the system. As this study confirmed, with the use of the fuzzy reinforcement learning approach, all subsystems were stable.

The schematics of the above-proposed control is presented in Fig. 22.9. The output of the fuzzy controller is the input to the open-link locomotion module model. At the same time, the reinforcement learning part is used to provide the optimal parameters of the fuzzy controller. The reward and tuning process of the fuzzy reinforcement learning controller is presented in [6] in detail.

The results of the simulations are given in Fig. 22.10. The results testify that the application of fuzzy logic itself may cause fluctuations or longer transients of the rotational velocity if the locomotion module's wheel. This is due to the fact that

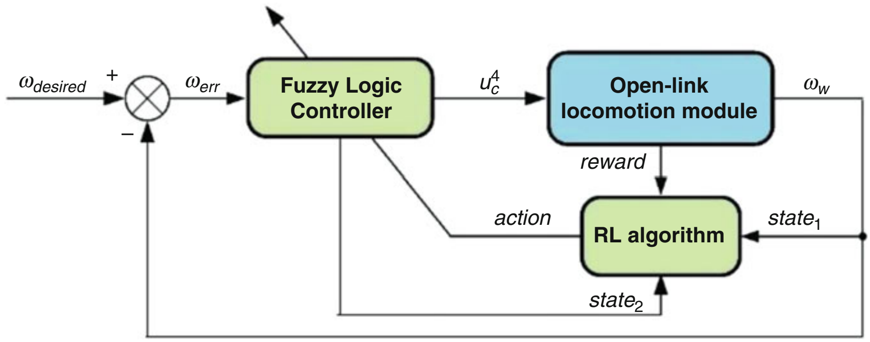

Fig. 22.9 Block diagram of the closed loop control system of the locomotion module

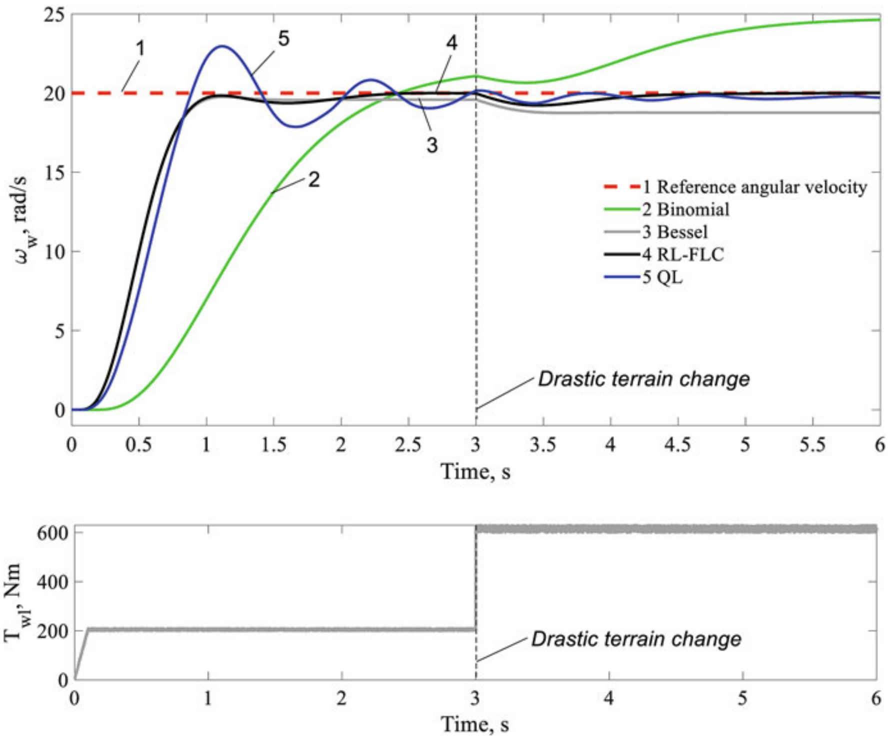

Fig. 22.10 Simulation results of wheel torque load and the wheel angular velocity control by different control methods (*1* – reference angular velocity, *2*, *3* – actual angular velocities controlled by single Binomial and single Bessel; *4* – actual angular velocity controlled by RL-FLC; *5* – actual angular velocity controlled by Q-learning)

the final conditions may differ (due to, for instance, additional external disturbances, etc.) from the conditions at which the system has been trained. At time of t = 3 s, a drastic terrain change occurs, which influences the wheel torque (see Fig. 22.10). However, the designed fuzzy reinforcement controller is robust and agile enough to overcome this dynamic change without significant oscillations of the rotational velocity of the wheel.

An analysis presented in [6] proved that the computational time of the control algorithm allows for running the control in real-time computations. Thus, the system of the designed state observer, the fuzzy reinforcement learning controller, and the fuzzy corrector is fast to operate within the time interval of the longitudinal relaxation time constant.

22.8 Conclusions

The technical problem of the improving of tyre mobility in severe terrain conditions has been solved by designing an agile tyre mobility control system that comprises a state observer, a fuzzy reinforcement controller, and a fuzzy corrector. The control system was designed for the locomotion module and computational simulations were conducted. The simulations proved the ability of the control system to operate in real-time within the longitudinal relaxation time constant when the tyre and soil are gaining the longitudinal deflections and an extended slippage did not occur yet. In future research plan, the designed control will be extended to a hybrid computer simulation of a 4×4 truck when one of the wheels in simulation is substituted with a physical wheel that simultaneously runs on the MTS FlatTrac LTR.

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