

Advancement of Vehicle Dynamics Control with Monitoring the Tire Rolling Environment

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ABSTRACT

One of the most important challenges for electronic stability control (ESC) systems is the identification and monitoring of tire rolling environment, especially actual tire-road friction parameters. The presented research considers an advanced variant of the ESC system deducing the mentioned factors based on intelligent methods as fuzzy sets.

The paper includes:

- Overview of key issues in prototyping the algorithms of Electronic Stability Control.
- Case study for vehicle model.
- Procedures for monitoring of tire rolling environment: theoretical backgrounds, computing methods, fuzzy input and output variables, fuzzy inference systems, interface with ESC algorithm.
- Case study for ESC control algorithm.
- Examples of simulation using Hardware-in-the-Loop procedures.

The proposed approach can be widely used for the next-generation of ESC devices having the close integration with Intelligent Transport Systems.

INTRODUCTION

Embedded electronic systems are the binding attributes of modern vehicles. The most important cluster of these systems relates to the integrated vehicle dynamics control making a substantial positive impact to the driving safety. Electronic stability control systems play here significant role.

An analysis of road accidents from United States, European, and Japanese sources showed that the electronic systems for

the stability control allow reducing the collisions with lethal outcomes on 30-50% for cars and on 50-70% for off-road passenger vehicles. At that, the rollover probability can be decreased on 70-90% [1].

One of the first regulating documents for vehicle dynamics control is the SAE standard J2564 "Automotive Stability Enhancement Systems" defining the main functions of the system, its variants, and ESC architecture [2]. In accordance with the SAE standard J2564, 20+ acronyms for the stability control systems are known today. This is because each of manufacturers has been introduced an original designations to protect its own trademark. Next step in standardization activities belongs to the Federal Motor Vehicle Safety Standard No. 126 [3]. This document gives more detailed system description, set of required functions etc.

Both documents have contributed to the preparation for the Amendment No. 11 to the UN/ECE Regulation No. 13 [4]. Now many classes of vehicles are obliged with the mandatory installation of ESC systems, with introduction dates in the near future.

One of the crucial problems for modern ESC systems is the determination of longitudinal and lateral velocities of a vehicle. The second key challenge is predicting possible changes in the driving environment and sequentially devising a strategy for pre-emptive vehicle control. These issues relates to a reliable estimation of tire-road friction parameters. The structure of this paper centers in this subject matter, including the description of fuzzy methods for tire-road friction identification.

The results of Hardware-in-the-Loop-simulations as applied to vehicles as components of Intelligent Transport System illustrate the proposed fuzzy control. This research advances the results obtained by the author and published in [5, 6].

DEVELOPMENT OF ESC ALGORITHMS

Research on the development of Electronic Stability Control algorithms covers several topics. Most important of them are connected with the following issues.

Vehicle Design: The ESC system should keep the trajectory set by the driver. For this purpose, the ESC system can influence the engine torque and brake moments. An indirect task of ESC algorithm is to estimate the yaw moment required for the correction of vehicle trajectory [7, 8]. This task, being always individual for a specific type of vehicle, is necessary to adjust the control actions depending on powertrain architecture, steerability and other design parameters of the vehicle.

Integration with vehicle systems: Nowadays many variants of the ESC integration with various automotive systems are known. One of examples is the embedding functions of active front steering (AFS) into the vehicle dynamics control [9]. Such an integrated system can essentially improve the vehicle stability and maneuverability due to the optimized coordination of individual chassis control modules of ESC and AFS. One more tendency lies in the integration of ESC functions with systems of wheel torque distribution. These devices use the active power-dividing units, and they belong to the most promising engineering solutions for vehicle dynamics control [10].

Control methods: ESC algorithms must accurately compute the reference yaw rate or boundary conditions for the yaw rate. This information is required for subsequent assessment of yaw rate sensor signals as well as for the calculation of sideslip angle from the longitudinal and lateral vehicle velocities.

Most of known ESC systems use the Kalman filter for computing both yaw rate and velocities. This is a recursive filter estimating the state of a dynamic system from actual measurements and previous filter conditions. The Kalman filter uses an error-squared criterion that requires information about the covariance matrices of measurement- and disturbance-related noises as well as an initial value of the covariance matrix to predict the state vector errors. This information can be handled through diverse approaches. For example, in the work [11] the measurement noise and process noise covariance matrices are dynamically calculated or recomputed during the filter operation. To improve the algorithm robustness, other methods propose also advancements of the Kalman filter with the nonsensitivity band for control deviations, sensor bias compensation, road bank angle compensation, surface friction estimation, or blending of control terms [12, 13].

Choice of control philosophy: Analyzing the state-of-the-art in ESC algorithms, the following attributes of vehicle dynamics can be defined as control parameters:

- Sideslip angle and its deviation from permissible value;
- Lateral acceleration and its rate;
- Lateral wheel slip value and differences in slip values between wheels;
- Yaw angle and yaw rate.

In addition, the system should assess the control efficiency through maximal angle of steering wheel required to keep the vehicle trajectory set by the driver.

ESC systems use mainly the lateral acceleration and the yaw rate as basic control parameters because the direct acceleration and yaw signals can be received from corresponding sensors. Figure 1 shows prevailing combinations of vehicle parameters forming the control philosophy of ESC systems. In spite of the key role of yaw rate, consideration of the lateral acceleration and vehicle sideslip angle enhances the vehicle stability by driving on low-friction roads [14].

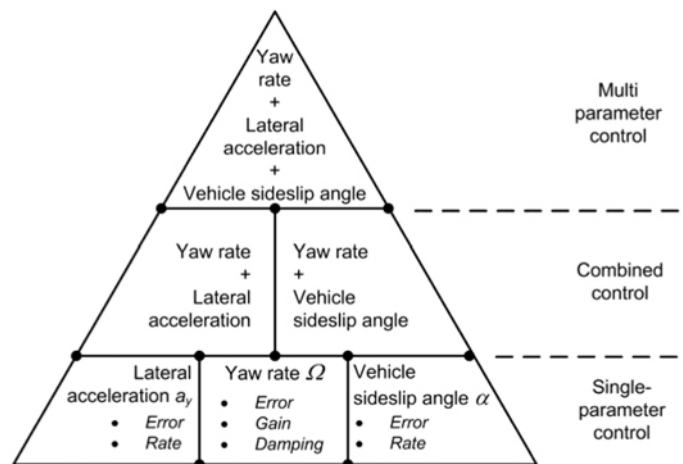


Figure 1. Control parameters of ESC systems

Accounting road parameters: The performance of vehicle dynamics control can be substantially improved with the forecasting and monitoring functions for road conditions. Most of modern systems use the correlation dependencies obtained by preliminary tests of different tires on diverse road surfaces. The tire dynamic models can be also applied for this purpose. Another approach, discussed in this work, use the fuzzy sets theory and fuzzy controllers allowing high estimation accuracy of actual road conditions in identification algorithms [15].

Taking into account given reasoning, next chapters discuss an advanced control philosophy for ESC systems.

ADVANCED CONTROL STRATEGY FOR ESC SYSTEM

ALGORITHM STRUCTURE

The generic structure of the algorithm is given in Figure 2. It has elements of fuzzy identification for the actual road parameters to choose the control thresholds for the braking forces in the ESC system. The fuzzy procedures are also used for the yaw rate, vehicle sideslip and lateral acceleration to deduce the control signal for the subsequent definition of the wheel or wheels to be controlled.

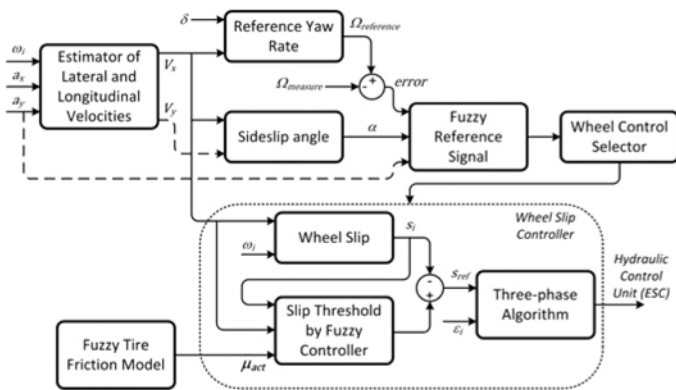


Figure 2. Algorithm structure

δ - steering angle, $\Omega_{reference}$ - computed yaw rate, $\Omega_{measure}$ - measured yaw rate, err - yaw rate error, α - slip angle, a_x - longitudinal vehicle acceleration, a_y - lateral vehicle acceleration, ω_i - angular velocities of wheels, s_i - computed wheel slips, s_{ref} - reference slip, ε_i - angular deceleration of wheels

The main steps of the control algorithm are as follows.

1) The “Estimator of Longitudinal and Lateral Velocities” calculates the velocities from the accelerometers and wheel rotation velocity sensors and using an extended Kalman filter [11].

2) The reference yaw rate and vehicle sideslip are computed from the calculated velocities [16].

3) The controller “Fuzzy Reference Signal” determines the control signal from the yaw rate error, sideslip, and lateral acceleration. From this signal, the block “Wheel Control Selector” identifies the wheel or wheels required the brake control force to ensure vehicle stability, and the rate of this force [17].

4) The wheel slip controller, as a substantial part of the ESC System, processes the information about requiring brake control forces. The block “Slip Threshold by Fuzzy Controller” uses the actual value of the tire-road friction coefficient μ_{act} from the fuzzy tire friction model as well as the calculated wheel slips s_i to reconstruct the friction-slip curve and to find an optimum slip threshold. Next, the block “Three-phase Algorithm” determines the control signals for the hydraulic control unit of the ESC system to perform the control actions on the wheel brakes.

THE VEHICLE MODEL FOR CONTROL ALGORITHM

The vehicle model has four degrees of freedom (DOFs) for spatial motion and two additional rotational DOFs for wheel rotation about their spin axes. This approach leads to the model with a total of 12 DOFs. In accordance with the schemes shown in Figure 3, the vehicle motion can be described by the following equations:

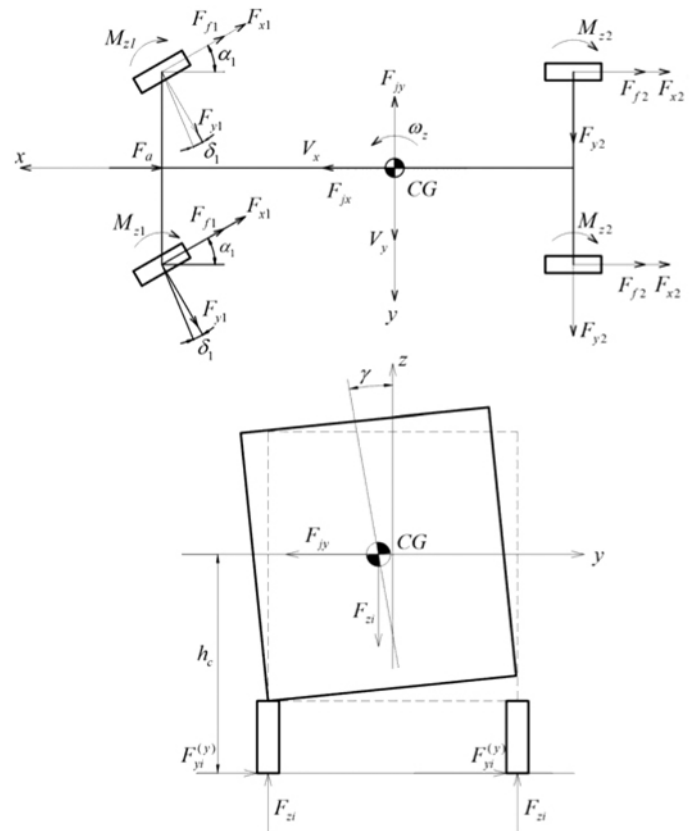


Figure 3. Vehicle model scheme

$$m_a (\dot{V}_x - V_y \Omega) = \sum_{i=1}^4 (F_{xi} \cos(\delta_i) - F_{fi} \cos(\delta_i) - F_{yi} \sin(\delta_i)) - F_A \quad (1)$$

$$m_a (\dot{V}_y + V_x \Omega) + m_s h_s \ddot{\theta} = \sum_{i=1}^4 (F_{xi} \sin(\delta_i) - F_{fi} \sin(\delta_i) + F_{yi} \cos(\delta_i)) \quad (2)$$

$$I_z \dot{\Omega} = \frac{B}{2} \sum_{i=1,3} (F_{xi} \cos(\delta_i) - F_{xi+1} \cos(\delta_{i+1}) - F_{\beta} \cos(\delta_i) + F_{\beta+1} \cos(\delta_{i+1}) - F_{yi} \sin(\delta_i) + F_{yi+1} \sin(\delta_{i+1})) + (a - l_i) \sum_{i=1,3} (F_{xi} \sin(\delta_i) + F_{xi+1} \sin(\delta_{i+1}) - F_{\beta} \sin(\delta_i) - F_{\beta+1} \sin(\delta_{i+1}) + F_{yi} \cos(\delta_i) + F_{yi+1} \cos(\delta_{i+1})) - \sum_{i=1}^4 M_{zi} \quad (3)$$

$$I_x \ddot{\theta} + m_s h_s (\dot{V}_y + V_x \Omega) + c_\theta \dot{\theta} + k_\theta \theta = \left(\sum_{i=1}^4 (F_{yi} \cos(\delta_i) - F_{xi} \sin(\delta_i) - F_{fi} \sin(\delta_i)) \right) h_s \quad (4)$$

where F_{xi} are the longitudinal tire forces, F_{yi} are the lateral tire forces, δ_i are the turn angles, F_{fi} are the tire rolling resistance forces, M_{zi} are the turning resistance moments, F_A is the longitudinal aerodynamic resistance force, m_a is vehicle mass, m_s is vehicle sprung mass, V_x is longitudinal velocity, V_y is lateral velocity, Ω is yaw rate, θ is roll angle, k_θ is suspension damping, c_θ is suspension stiffness, h_s is roll height, B is the track, a and l_i are the distance between the vehicle centre of gravity centre and the vehicle axle.

The main equations for wheel dynamics are:

$$J_w \dot{\omega}_{1i} = -k_{wi} (\phi_{1i} - \phi_{2i}) - c_{wi} (\omega_{1i} - \omega_{2i}) - T_{wi}^{br} \\ J_w \dot{\omega}_{2i} = k_{wi} (\phi_{1i} - \phi_{2i}) + c_{wi} (\omega_{1i} - \omega_{2i}) + (F_{xi} + F_{fi}) r_{wi} \quad (5)$$

where J_w is the wheel inertia, c_{wi} is the longitudinal tire stiffness, k_{wi} is the longitudinal tire damping coefficient, T_{wi}^{br} is the brake wheel torque, ϕ_{1i} and ω_{1i} are rotation angle and angular velocity of wheel axle, ϕ_{2i} and ω_{2i} are rotation angle and angular velocity of tire casing.

The model for forming the longitudinal and lateral tire forces uses Dugoff's model procedures [18]:

$$F_{xi} = \frac{c_{wi} s_i}{1 - s_i} f(\lambda_i) \quad (6)$$

$$F_{yi} = \frac{c_{yi} \tan \alpha_i}{1 - s_i} f(\lambda_i) \quad (7)$$

where c_{yi} is the lateral tire stiffness, s_i is slip rate, α_i is sideslip angle, and $f(\lambda_i)$ is defined as:

$$f(\lambda) = \begin{cases} \lambda(2 - \lambda), & \text{if } \lambda < 1 \\ 1, & \text{if } \lambda > 1 \end{cases} \quad (8)$$

and λ should be calculated as:

$$\lambda_i = \frac{\mu_{acti} F_{zi} (1 - s_i) (1 - e_r \sqrt{s_i^2 + \tan^2 \alpha_i})}{2 \sqrt{(c_{wi} s_i)^2 + (c_{yi} \tan \alpha_i)^2}} \quad (9)$$

where μ_{acti} is the actual tire-road friction coefficient, F_{zi} is normal tire force, e_r is the road adhesion reduction coefficient.

This system of equations makes possible to find all the control parameters required for the ESC algorithm. However, the procedure of finding the actual tire-road friction coefficient remains to be solved. For this purpose, authors have developed novel approach based on fuzzy sets. This method is discussed next.

UNCERTAIN CHARACTER OF TIRE-ROAD FRICTION

The key challenge for the ESC systems is predicting possible changes in the driving environment and sequentially devising a strategy for pre-emptive vehicle control. With regard to vehicle-road interaction, the prediction activities come up against the problem of uncertainty. Within the research literature, the term "uncertainty" is used for the inherent unknown quantities present in decisions. Two kinds of uncertainty [19] are present in tasks for dynamic vehicle control:

- 1). Data uncertainty: illogical or surprising discrepancy between data and characteristics represented by data.
- 2). Model uncertainty. This aspect relates to the representation of an object in the form of a model with certain levels of abstraction. The issue in this context is the uncertainty in the choice of model parameters and subsequent mapping.

A literature survey shows that this subject matter has been investigated most of all with regard to a number of vehicle dynamics problems:

- Construction of generic vehicle models [20, 21];
- Estimation of friction and slip parameters for tire-road interaction [22, 23];
- Active safety applications and driver assistance [24, 25].

It follows from the analysis of the literature and of the technological solutions realized in up-to-date control systems that the statistical instruments, especially Gaussian processes and Monte-Carlo methods, are mainly proposed to overcome the uncertainty by simulation. This approach is warranted in

the case of the possible long-term observation of an object while gathering a wide range of experimental data.

A different challenging topic arises when the prediction of the object's reaction to an uncertain environment is required. The presented work discusses how this matter can be handled with methods based on fuzzy sets. The application of fuzzy logic to problems of tire-road interaction has its own research tradition. Kiencke and Daiß were amongst the first to consider these intelligent methods [26]. Subsequently, fuzzy logic has received wide acceptance in traction, brake and suspension control [27,28,29,30,31]. The problems of fuzzy vehicle dynamics and simulation being considered next preceded the authors' own investigations [15, 32, 33].

Among many tire parameters, the overcoming of uncertainty is of particular value for tire friction. Both the tire friction coefficient μ and the tire force ratio μ_x and μ_y are involved in any vehicle dynamics control procedures, and the ambiguous interpretation of these factors can negatively affect the control process.

From fundamental work [34,35,36,37], the main factors of uncertainty for tire friction are outlined in Table 1. Of course, an objective tire friction model requires a consideration of many other dynamic parameters such as wheel loading, tire inflation etc., but only the most characteristic issues are discussed next.

Taking a view on tire friction models within vehicle control applications, it is necessary to differentiate between two kinds of vague situations.

Table 1. Examples of crisp and uncertain components in tire friction models

Velocity	<i>Crisp</i> : increasing the velocity reduces the friction parameters
Road texture	<i>Crisp</i> : friction parameters grow both with the depth of pure micro- or macro-texture <i>Uncertain</i> : the influence of mixed surface is difficult-to-define
Water film	<i>Crisp</i> : the water film reduces the friction coefficient in general <i>Uncertain</i> : the effect of the water film depends on the velocity and road surface texture
Snow thickness	<i>Uncertain</i> : depending on level of snow compaction, the tire friction can be subject both to a firm surface and loose surface contact models
Contact temperature	<i>Crisp</i> : increasing the tire-surface contact temperature reduces the friction coefficient

Numerical uncertainty is applicable to situations when unexpected oscillations of friction value arise from steady, unchanging conditions of tire rolling. For example, if the on-board tire model of a control system operates with a confidence interval $\mu = [0.7...0.9]$ for dry roads, and the computed μ -value by the vehicle driving on a homogenous, plain asphalt road leaves this interval, then the resulting uncertainty can be caused by:

- Inaccuracy of sensor-based estimation of input variables, for instance, wheel angular velocities;
- Wrong choice of coefficients in the case of empirical models ("Magic Formula" tire model or similar).

Linguistic uncertainty is a fundamentally new problem in relation to vehicle dynamics control. This concept is applicable to situations when the system correctly recognizes that an output variable is changing (for instance, tire friction or tire force ratio) but is not able to treat this information properly in the control algorithm. For example, the friction drops during vehicle motion from 0.8 to 0.2. The value of $\mu = 0.2$ can refer equally to an icy road or to a surface with high water film.

Considering a typical vehicle dynamics control system, the belonging of the μ -value to a specific surface type is non-essential. However, for intelligent automotive systems with prediction tasks or for devices at the driver-vehicle-interface, this information is of special importance. Knowing the surface type, such a system can predict the propagation of a critical driving situation and perform feed-forward control actions. With regard to the above-mentioned case, for icy roads, the brake control system should be prepared for possible emergency braking, and for the surface with high water film the speed should be reduced to avoid aquaplaning.

It should be mentioned that the implementation of linguistic uncertainty into the procedures of vehicle control primarily opens new opportunities by supporting the ESC systems through off-board information delivered by Intelligent Transport Systems (ITS).

APPLICATION OF FUZZY SETS TO TIRE FRICTION MODELS WITH UNCERTAINTY

FUZZY STATEMENTS

A number of well-established and novel methods of uncertainty modeling are known in different areas of science and technical applications. The choice of fuzzy logic as the basic analytical tool is due to its good applicability to tire dynamics problems both for short-term and long-term processes. The fuzzy models primarily allow dynamic variables to be deduced not only from direct but also from indirect indicators. This procedure is further illustrated

through the assessment of road friction from environmental parameters. Of special interest for uncertainty problems is that fuzzy methods have elements of self-learning. They provide a permanent adaptation of a universal tire model to new facets of tire-road interaction during the rolling process.

It is anticipated that the audience of this paper has basic knowledge about fuzzy logic. Nevertheless, some notions should be explained.

A conventional control system operates with crisp statements, for example: “Tire friction coefficient is 0.1”. This proposition can be obtained with any general tire model and it has minimal information capacity.

The simple fuzzy statement can be as follows: “Tire friction coefficient is around 0.1”.

It can be derived from the simplest fuzzy model with the subsequent advance of a direct extended fuzzy proposition: “Tire friction coefficient around 0.1 conforms to ice”. This model is more informative because there is a linguistic link between the physical magnitude of friction and road type.

An alternative is the indirect extended fuzzy statement: “Tire friction coefficient on ice is around 0.1”. This proposition has linguistic feedback, which allows the use of off-board physical quantities for the problems of tire dynamics. It can be, for example, the texture of the road surface or weather conditions.

Hence, fuzzy logic can provide solutions to identification and prediction problems related to tire-surface interaction. For instance, direct extended fuzzy propositions allow the identification of surface type, and indirect extended fuzzy statements allow the numerical values of the corresponding friction coefficient to be forecast.

Explanation of fuzzy sets

The process of fuzzy interpretation of tire friction parameters is illustrated below with the main steps that are followed. Next, the input and output variables will be described in the form of fuzzy sets. Assuming that a finite set

$$X = \{x\} \quad (10)$$

can be found for each of these model variables, a corresponding fuzzy subset A of X is:

$$A = \{x, \theta_A(x)\} \text{ for } x \in X \quad (11)$$

The relation $\theta_A(x)$ in expression (11) is the membership function. This describes how the element x is related to subset A . The membership value of A is mapped over the interval $[0, 1]$.

If $\theta_A(x) = 1$ then x belongs fully to the fuzzy subset A , if $\theta_A(x) = 0$ then x does not belong to the fuzzy subset A . Within $0 < \theta_A(x) < 1$, x belongs partially to the fuzzy subset A . To describe these relations, the graphical representation of membership functions is used. As an example, Figure 4 shows the membership functions for some abstract set M of tire friction coefficients μ_i :

$$M = (\mu_1, \mu_2, \dots, \mu_n). \quad (12)$$

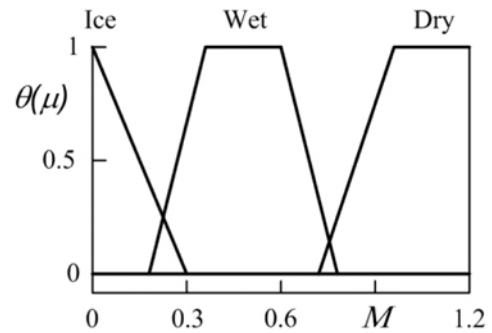


Figure 4. Illustrative example of graphical representation of fuzzy membership functions

It is logically necessary to divide the set of values over several intervals (subsets). For illustrative purposes only, Figure 4 gives a very simplified division as an example: “Ice” for ice-covered road; “Wet” for a wet surface; “Dry” for a dry road. Here “Ice”, “Wet” and “Dry” are linguistic variables. Any choice of such a name is a matter of convention; they might be “Road type 1”, “Road type 2”, “Road type 3”, or “Small”, “Medium”, “High”, or similar. The related M fuzzy subsets can be described as:

$$\begin{aligned} A_{ice} &= \{\langle \mu_1, \theta_{A_{ice}}(\mu_1) \rangle, \langle \mu_2, \theta_{A_{ice}}(\mu_2) \rangle, \dots, \langle \mu_n, \theta_{A_{ice}}(\mu_n) \rangle\}, \\ A_{wet} &= \{\langle \mu_1, \theta_{A_{wet}}(\mu_1) \rangle, \langle \mu_2, \theta_{A_{wet}}(\mu_2) \rangle, \dots, \langle \mu_n, \theta_{A_{wet}}(\mu_n) \rangle\}, \\ A_{dry} &= \{\langle \mu_1, \theta_{A_{dry}}(\mu_1) \rangle, \langle \mu_2, \theta_{A_{dry}}(\mu_2) \rangle, \dots, \langle \mu_n, \theta_{A_{dry}}(\mu_n) \rangle\}. \end{aligned} \quad (13)$$

Each fuzzy subset has its own graphical interpretation. Referring to Figure 4, the so-called Z-shaped function describes “Ice”, trapezoidal function - “Wet”, and S-shaped function - “Dry”. The other most frequently used types of membership functions can have triangular, trapezoidal, and bell-shaped or Gaussian forms. The input and output variables of fuzzy tire models discussed below use different types of membership functions. Choosing the appropriate type, the following principles have been taken into account: