Boada, B.L., Boada, M.J.L., Gauchía, A. et al. Sideslip angle estimator based on ANFIS for vehicle handling and stability. *Journal of Mechanical Science and Technology* (2015) 29: 4, 1473-1481. https://doi.org/10.1007/s12206-015-0320-x

# SIDESLIP ANGLE ESTIMATOR BASED ON ANFIS FOR VEHICLE HANDLING AND STABILITY

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**ABSTRACT–** Most of the existing ESC (Electronic Stability Control) systems rely on the measurement of both yaw rate and sideslip angle. However, one of the main issues is that the sideslip angle cannot be measured directly because the sensors are too expensive. For this reason, sideslip angle estimation has been widely discussed in literature. The modeling of sideslip angle is complex due to the non-linear dynamics of the vehicle. This work proposes a new methodology based on ANFIS to estimate the vehicle sideslip angle. The estimator has been validated by comparing the proposed ANFIS prediction model with the values provided by CARSIM model, which is an experimentally validated software. The advantage of this estimation is the modeling of the non-linear dynamics of the vehicle by means of signals which are directly measured from vehicle sensors. The results show the effectiveness of the proposed ANFIS-based sideslip angle estimator.

**KEY WORDS**: Neuro-fuzzy systems; Vehicle Stability; vehicle handling; Sideslip Estimation

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## 1. INTRODUCTION

With the recent advancements in the vehicles industry, driving safety in passenger vehicles is considered one of the key issues in designing any vehicle. According to other studies, Electronic Stability Control (ESC) is considered to be the greatest road safety innovation since the seatbelt. Hence, the market demands more research to improve the performance of these systems.

To improve the vehicle handling and stability based on ESC, the yaw rate (the yaw velocity of the chassis) and the vehicle sideslip angle (the angle between the directions of the vehicle's velocity and its chassis) are controlled to follow their target values [1,2]. The yaw rate can be directly measured by a yaw rate sensor (gyroscope) [3,4]. In addition, the sideslip angle can be directly measured via optical or GPS sensors [5,6,7]. However, the drawbacks of measuring the yaw rate and the sideslip angle are accuracy, reliability and cost [8]. Sideslip angle cannot be directly measured using standard sensors, therefore, it must be estimated by means of an observer [9,10,11]. For this reason, an accurate estimation of the vehicle's sideslip angle is highly essential for applications in vehicle dynamics and control.

Sideslip angle estimation has been widely discussed in the literature. The modeling of sideslip angle is complex due to the non-linear dynamics of the vehicle. Some authors employ physical models for the estimation of sideslip angle [12,13,14,15]. Most mentioned methods are based on the bicycle dynamic model or its variations. These models generate noise free sideslip angle estimations, but can be sensitive to changes in the vehicle parameters. Other authors use kinematics based-models which consider the motion of a body, which are not affected by the uncertainties [14,16,17]. These methods integrate the derivative of the sideslip angle calculated from sensor signals including yaw rate, lateral acceleration and vehicle speed. Satisfactory robustness of tire properties, road friction and vehicle parameters, such as vehicle mass and moment of inertia, can be achieved. Finally, other authors use combined methods which bring together the advantages of the previous two methods [9,11].

Other authors propose methods for designing observers in order to estimate the sideslip angle from variables that can be easily measured, such as yaw rate, lateral acceleration and velocity. Different models (such as linear [18] and nonlinear [19]), and observers (such as Kalman Filters [10,20], RLS algorithms [21], Luenberger observers [22]) have also been considered to estimate the sideslip angle. A common feature of most of these observers for the estimation of the sideslip angle is that they heavily rely on an accurate tire model, which may vary during vehicle operation.

Some authors use algorithms based on artificial intelligence to estimate the sideslip angle such as Fuzzy [23] and Neural Networks [24] to avoid issues associated with the identification and adaptation of reference model parameters. Artificial intelligence has also been used in the field of vehicles obtaining satisfactory results [25,26,27].

In this work, a method based on Adaptive Neuro-Fuzzy Inference System (ANFIS) is proposed in order to estimate the vehicle sideslip angle. The ANFIS controller combines the benefits of both Neural Networks and Fuzzy logic. The former is adaptive and can learn from generalization and pattern recognition. The latter allows soft and steady performance [28]. In [29], an ANFIS algorithm is proposed to estimate the yaw rate, providing good results.

CarSim results obtained after training show that the ANFIS model learns to estimate the sideslip angle behavior properly without difficulty and reliably.

## 2. VEHICLE MODEL

CarSim software has been employed to test the effectiveness of the proposed algorithm [30] and its used has become a widespread simulation software in the automotive industry. The software combines traditional and modern multi-body vehicle dynamics, based on parametric modeling. The software includes three-part graphic database of a full-vehicle model, direction and speed control and external conditions, such as, road information, drag, etc.

The estimation algorithm, based on ANFIS, presented in this work has been evaluated using a typical C-class hatchback car, available in the CarSim library, having 205/55 R16 tires (Figure 1).

Table 1 shows the Hatchback vehicle parameters such as mass, wheel base, tire radius, and moments of inertia.

## 3. VEHICLE SIDESLIP ANGLE ESTIMATION

The sideslip angle of a vehicle (β) is the angle between the orientation of the vehicle and the direction of travel at the center of gravity (COG) (see Figure 2). It is defined as:

$$\beta = \frac{V_x}{V_y} \qquad (1)$$

where $V_x$ is the longitudinal velocity and $V_y$ is the lateral velocity of vehicle.

The measurement of sideslip angle is necessary for many vehicle control systems. Due to a lack of accuracy and cost, this parameter cannot be directly measured.

### 3.1. Estimator design based on ANFIS

Since physical-observers are based on a reference vehicle model, it is possible to provide a satisfactory estimation when vehicle model parameters are accurately known.

An alternative to physical models are non-parametric ones, which are able to model an accurate response behavior, while providing considerable flexibility and without the need of a physical meaning of its parameters. For this reason, an ANFIS-based observer for sideslip angle estimation is proposed.

Adaptive Neuro-Fuzzy Inference System (ANFIS) systems are a type of adaptive networks that are functionally equivalent to fuzzy inference systems. In other words, it is an advanced artificial intelligence technique that uses Neural Networks to construct automatically a Fuzzy Logic Estimator (FLE) for each specific case. Prior to the generation of the estimator by the Neural Network, training of the network with data that represents the desired performance of the estimator, must be performed. The learning process of the neural network is based on trial and error, generating an FLE that mimics the desired performance.

The advantage of using the ANFIS technique is that it combines the benefits of both Neural Networks and Fuzzy logic. The former has the advantage of being adaptive and the ability to learn by generalization and pattern recognition. The latter allows a soft and steady performance [28].

During the past ten years neural networks (NN) have attracted a great deal of attention in vehicle dynamics and control [31, 32]. Neural networks have been effectively applied to model complex systems due to their good learning capabilities.

ANFIS uses a Takagi-Sugeno fuzzy inference method in contrast with the model that uses the Mamdani method. Takagi-Sugeno is more compact and computationally more efficient than the Mamdani system. Furthermore, it is more flexible, being especially suitable for adaptive modeling techniques. However, the Mamdani system is more intuitive and understandable by the human side [33].

Having an FLE at this point has many pros, some of which are:

1. It provides a smooth estimating performance.
2. It is able to characterize non-linear behavior.
3. It can be implemented in real time.
4. It can easily be integrated.

3.1.1. Training data

The selection of training data is a crucial process. These data should contain all of the required representative features. In this case, different maneuvers are selected in order to characterize the linear and non-linear vehicle behavior [24].

A total of 80 experiments were designed and carried out for J-turn maneuvers at different speeds (30 km/h, 65 km/h, 100 km/h and 130 km/h), steering angles in the clockwise and anti-clockwise direction (45 deg, 75 deg, 100 deg, 125 deg and 150 deg) and friction coefficient (low and high). Table 2 summarizes the maneuvers considered during the training step.

3.1.2. Input data

Not only does the training data ~~influences~~ on the obtained ANFIS-based observer. but also on the selection of input data. An excessive number of inputs not only impairs the transparency of the underlying model, but also increases the computational complexity for building the model.

The criteria considered to select the inputs for the ANFIS algorithm are:

- To select the minimum number of inputs.
- To select signals that can be measured by onboard vehicle sensors.

Considering the previous criteria and signals employed in typical sideslip angle observers [14,15], three groups of input data have been selected:

1. First group:
    - Lateral acceleration.
    - Yaw rate.
    - Steering angle.
    - Longitudinal velocity.
2. Second group:
    - Lateral acceleration.

- Yaw rate.
- Steering angle.
- Longitudinal velocity.
- Yaw rate/Longitudinal velocity.

3. Third group:
   - Lateral acceleration.
   - Steering angle.
   - Yaw rate/Longitudinal velocity.

3.1.3. Architecture of NN and FLE

To generate the Fuzzy Logic Estimator (FLE) presented in this work, MATLAB ANFIS toolbox has been used. The neural network was generated and trained based on the data specified in the previous section. The network is trained and tested in order to prevent the learning algorithm from falling into a global minimum.

The network has been trained by means of a hybrid learning algorithm presented in [34]. This hybrid algorithm performs two phases at each learning stage, the first is a forward path learning technique that uses the least-squares learning technique and the second is the back-propagation learning algorithm.

For each input data, the NN is constructed for the observed sideslip angle. Afterwards, variations of the ANFIS toolbox options, such as, the number and type of fuzzy logic membership functions, the number of the ANN learning epochs (cycles), the error tolerance, etc., the fuzzy logic system, designed by trial and error, was chosen as the one that yield~~s~~ the least percentage of error.

Gaussian membership functions (gaussmf) were used to train ANFIS. For the first input group, four Gaussian membership functions (gaussmf) were used for each input. The number of generated FLE rules was 256. For the second input group, three Gaussian membership functions (gaussmf) were employed for each input. The number of generated FLE rules was 243. Finally, for the third input group, six Gaussian membership functions (gaussmf) were used for each input. The NN structure is shown in Figure 3. The number of generated FLE rules is 216. All of these NN were used to train ANFIS at 5 epochs.

Figures 5, 6 and 7 show the performance of the new ANFIS-constructed FLE on the training data for the first, second and third input group, respectively, where the blue data represents the desired testing data and the red data represents the output of the observer system. The average training error for each input group is 0.097 deg, 0.0986 deg and 0.1 deg, respectively.

After generating the FLEs, ~~and~~ new sideslip angle observer was tested with the testing data.

### 3.2. Testing data

Once the FLEs has run through the learning stage, it is necessary to test it on a series of maneuvers to verify the performance of the proposed algorithm. In Figure 7, the road test is shown. This test is carried out considering a road adhesion coefficient equal to 1 and with a vehicle velocity and steering wheel contour depicted in Figure 8 and 9, respectively.

Figures 11, 12 and 13 show the performance of the new ANFIS constructed on the cheking data for the first, second and third, respectively, where the blue data represents the desired data that the system should follow and the red data the output of the observer system. The average checking errors for each input group are 0.82 deg, 0.67 deg and 0.148 deg, respectively. ANFIS algorithms for input data 1 and 2 have a good interpolation ability in the range of the training data, however, they have a poor extrapolation capability. The ANFIS algorithm for input data 3 has a satisfactory interpolation and extrapolation ability.

## 4. DISCUSSION

Although ANFIS algorithm for input 3 has performed better than those for input groups 1 and 2, its reliability has been proved by comparison with other sideslip estimators. You et al. [15] indicated that the sideslip angle can be computed by the following equation:

$$\beta = \frac{-m \cdot a_y + \dfrac{b \cdot C_r - a \cdot C_f}{V_x} \cdot r + C_f \cdot \delta}{C_f + C_r} \qquad (2)$$

where $C_f$ and $C_r$ are the cornering stiffness of the front and rear axles; a and b are the distance from the center of gravity to the front and rear axles; m is the vehicle mass; $V_x$ is the longitudinal speed; $a_y$ is the lateral acceleration; r is the yaw rate and δ is the front wheel steering wheel.

Chung and Yi [14] propose the following sideslip angle observer:

$$\beta = \frac{\left(2 \cdot b \cdot (a+b) \cdot C_r \cdot C_f - m \cdot V_x^2 \cdot a \cdot C_f\right) \cdot \delta}{2 \cdot (a+b)^2 \cdot C_r \cdot C_f - m \cdot V_x^2 \cdot \left(a \cdot C_f - b \cdot C_r\right)} \qquad (3)$$

In order to demonstrate the improvement provided by the ANFIS observer,  a Kalman Filter observer was used for comparison. The optimal estimate of the state X, is given by:

$$\dot{X}_e = AX_e + Bu + K\left(y - CX_e\right) \qquad (4)$$

where X and y are the state and output vectors, respectively, A, B and C are the system, input and output matrices with constant parameters:

$$X = [V_y \quad r]^T$$
$$A = \begin{bmatrix} -(C_f + C_r)/(mV_X) & [-(aC_f + bC_r)/(mV_X)] - V_X \\ -(aC_f + bC_r)/(I_{zz}V_X) & -(a^2 C_f + b^2 C_r)/(I_{zz}V_X) \end{bmatrix}$$
$$B = [C_f/m \quad aC_f/I_{zz}]$$
$$C = \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix} \qquad (5)$$

Two Kalman Filters have been calculated considering diferent observer vectors:

- Kalman Filter 1D:

  $$y = [0 \quad r_{measured}]$$

- Kalman Filter 2D:

  $$y = [V_{y\_measured} \quad r_{measured}]$$

where $V_{y\_measured}$ is the lateral velocity and $r_{measured}$ is the yaw rate obtained from sensors.

The observer gain matrix, K, is given by:

$$K = PC^T R^{-1} \qquad (6)$$

where P is a symmetric positive definite solution of the algebraic matriz Ricatti equation:

$$AP + PA^T - PC^T R^{-1} CP + Q = 0 \qquad (7)$$

Q and R are symmetric and positive defined matrices describing noise intensities.

Finally, an estimator based on backpropagation NN (Neural Network) was used. The same training data, shown in Table 2, as the one employed for the ANFIS estimator, was used. The proposed network has a single hidden layer with 10 neurons and one output, which is the side slip angle. All neurons of the network use the hyper tangent activation function, since it has a range of (-1,1), which covers possible negative values of lateral acceleration, yaw rate, steering angle, longitudinal velocity and sideslip angle. The learning rate was initially set high and as training cycles were performed and the network was closer to the final solution, it was lowered. The NN was trained during 170000 cycles.

Figure 13 show the comparative results for the different algorithms.

It is worth highlighting that the performance of the ANFIS-based sideslip angle estimator has also been proved in maneouvres with different road conditions, such as, a lane change maneuver of a vehicle travelling at 90 km/h (see Figure 14) on a pavement with a friction coefficient of 0.8 and a J turn maneuver of a vehicle travelling at 80 km/h on a pavement with a friction coefficient of 0.5 (see Figure 15). Figure 16 shows the instantaneous error for a J turn maneuver for a vehicle travelling at 80 km/h on a pavement with a friction coefficient of 0.5. This figure demonstrates that the ANFIS algorithm has a good behavior for the transient zone compared to other algorithms.

Additional proof of the effectiveness of the proposed model, other than the graphical one, was performed by means of a quantitative analysis that takes into consideration the error for the different accomplished excitation conditions. The following equation has been used to represent the norm error as a function of time [35]:

$$E_t = \frac{\varepsilon_t}{\sigma_\beta} \tag{8}$$

where:

$$\varepsilon_t^2 = \int_0^T \left(\beta_{CarSim} - \beta_{estimated}\right)^2 \tag{9}$$

$$\sigma_\beta^2 = \int_0^T \left(\beta_{CarSim} - \mu_{beta}\right)^2 \tag{10}$$

where $\beta_{CarSim}$ represents the measured beta sideslip angle obtained from CarSim, $\beta_{estimated}$ is the estimated sideslip angle and $\mu_{beta}$ is the mean value of the sideslip angle obtained from CarSim during the period T.

The norm and maximum errors are provided in Table 3 and Table 4, respectively. The norm error supplies information about the state response and the maximum error about the transient response. It has been proved that the proposed ANFIS model provides a satisfactory performance. In addition, it is well suited for different training driving conditions and maneuvers and to analyze transient and steady-state response.

## 5. CONCLUSION

In this paper a new sideslip angle estimator is proposed based on ANFIS (Adaptive Neuro-Fuzzy Inference System). The advantage of this estimator is the modeling of the non-linear vehicle dynamics, which requires of sensor signals directly provided by vehicle sensors. The proposed method has been proved by means of CarSim sotware, which is a widespread and validated software employed in the automotive industry.

From the obtained results, it has been concluded that a suitable selection of the inputs to the ANFIS system is of paramount importance in order to accomplish the desired performance.

The model has been validated by means of a set of maneuvers that represent different driving and testing conditions. The model-based observers are suitable to estimate the side slip angle when road conditions correspond to the model parameters. This is the particular case in which road testing is performed with a friction coeffient equal to 1. In this case, similar errors are obtained for all methods. For the ANFIS-based estimator the obtained error is 0.25 and for the Kalman 1D-based estimator it is 0.26.

However, when the driving conditions do not correspond to the model parameters, then, errors are greater. This corresponds to a case in which a lane change and J-turn maneuvers with friction coefficient of 0.8 and 0.5, respectively, is performed. For these maneuvers the error obtained for ANFIS-based estimator is smaller than for the parameter model-based estimators, with the exception of Kalman 2D for the lane change maneuver. Since the model-observers are based on a reference vehicle model, they are able to provide a satisfactory estimate only if model parameters are accurately known.

On the other hand, the ANFIS-based estimator provides an error smaller than the NN-based estimator. The ANFIS-based estimator is adapts better in variable environments and learns by generalization.

Results have proved that the ANFIS-based estimator successfully estimates the sideslip angle for different driving conditions.

## 6.ACKNOWLEDGES

Authors gratefully acknowledge use of the services and facilities of the Research Institute of Vehicle Safety (ISVA) at Carlos III University and the the funds provided by the Regional Government of Madrid through the research project CCG10-UC3M/DPI-4614.

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Figure 15. Results for a J-turn maneuver for a vehicle travelling at 80 km/h on a pavement of friction coefficient of 0.5

Figure 16. Comparison error results for testing data among the proposed ANFIS-based sideslip angle estimator and common sideslip angle estimators for a J-turn maneuver for a vehicle travelling at 80 km/h on a pavement of friction coefficient of 0.5

Table 1. Vehicle parameters for thr C-Class hatchback car

| Symbol | Description | Value | Unit |
|---|---|---|---|
| $m_s$ | Sprung mass | 1274 | kg |
| $m_u$ | Unsprung mass | 142 | kg |
| $I_{xx}$ | Roll inertia | 606.1 | $kg{\cdot}m^2$ |
| $I_{yy}$ | Pitch inertia | 1523 | $kg{\cdot}m^2$ |
| $I_{zz}$ | Yaw inertia | 1523 | $kg{\cdot}m^2$ |
| a | Distance from front tire to COG | 1016 | mm |
| b | Distance from rear tire to COG | 1562 | mm |
| $R_w$ | Effective rolling radius | 310 | mm |
| h | Height of COG | 540 | mm |
| T | Wheel track | 1539 | mm |
| $K_s$ | Steering ratio | 17.5:1 | - |
| $C_f$ | Front tire cornering stiffness | 125167 | N/rad |
| $C_r$ | Rear tire cornering stiffness | 125167 | N/rad |

Table 2. Selected manouevres for training data

| Manoevres | Steer angle (deg) | Speed (km/h) | Friction coefficient |
|---|---|---|---|
| J turn | ±45 | 30, 65, 100, 130 | 0.3, 1 |
| J turn | ±75 | | |
| J turn | ±100 | | |
| J turn | ±125 | | |
| J turn | ±150 | | |

Table 3. Error norms for sideslip angle estimators

| | $E_t$ | | |
|---|---|---|---|
| | **Road testing** | **Chane Lane** | **J-turn** |
| **You et al.** | 0.286 | 1.18 | 2.18 |
| **Chu and Yi** | 0.516 | 1.17 | 2.03 |
| **Kalman 1D** | 0.26 | 1.08 | 3.85 |
| **Kalman 2D** | 0.31 | 0.36 | 3.11 |
| **NN** | 0.25 | 2.32 | 1.85 |
| **ANFIS** | 0.25 | 0.74 | 0.11 |

Table 4. Maximum errors for sideslip angle estimators

| | $E_{max}$ | |
|---|---|---|
| | **Chane Lane** | **J-turn** |
| **You et al.** | 0,32 | 0,64 |
| **Chu and Yi** | 0,27 | 0,62 |
| **Kalman 1D** | 0,29 | 1,17 |
| **Kalman 2D** | 0,10 | 0,94 |
| **NN** | 1,12 | 0,28 |
| **ANFIS** | 0,22 | 0,19 |

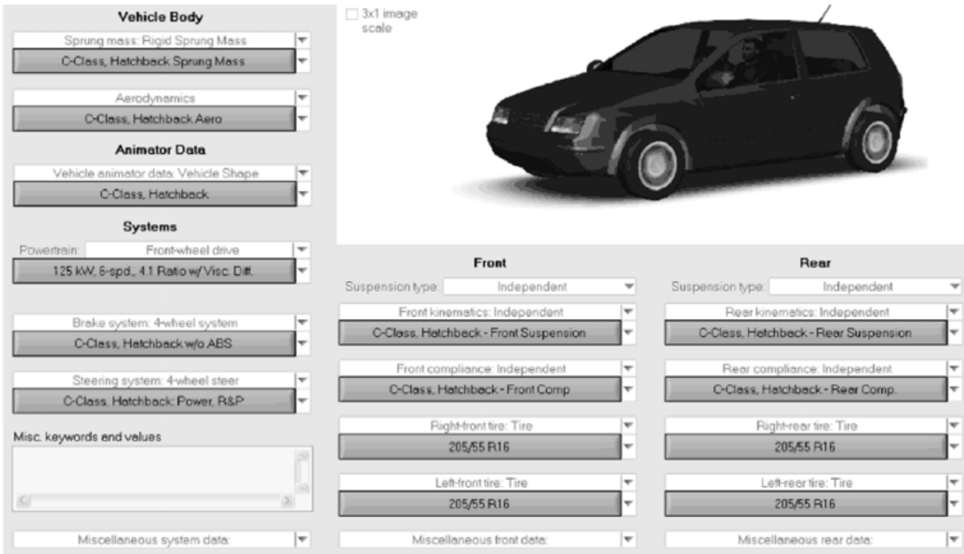


Figure 1. C-class hatchback car

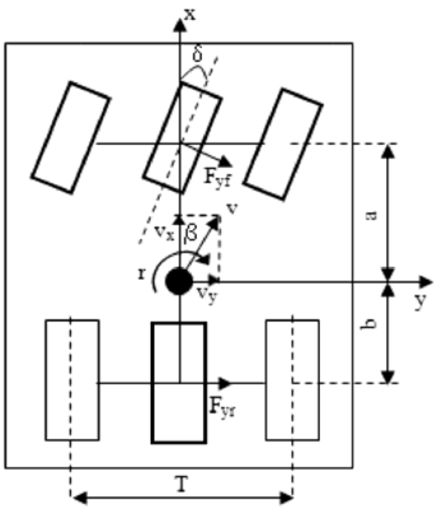


Figure 2. Vehicle parameters

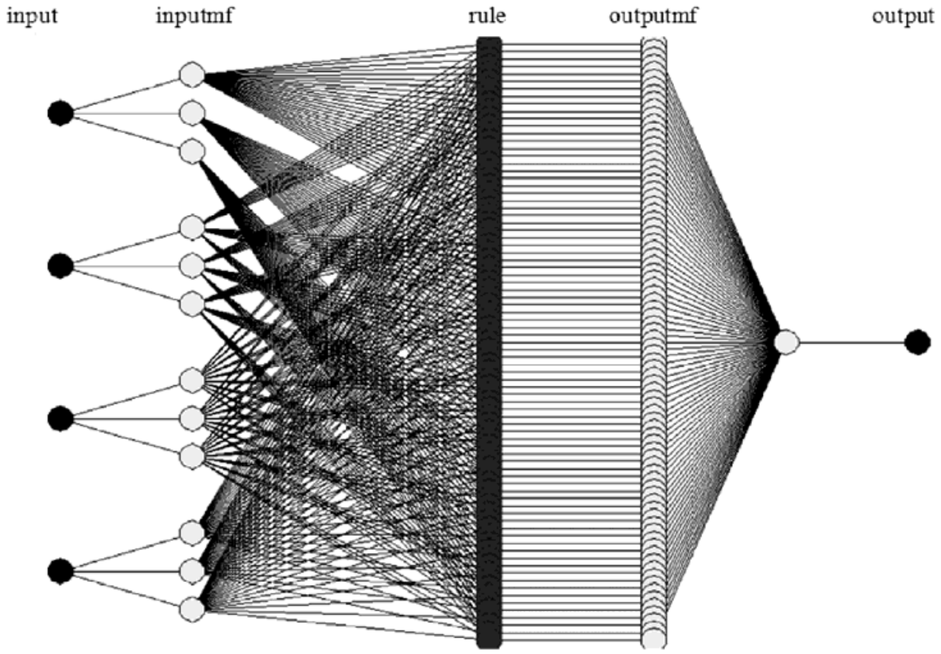


Figure 3. NN structure for the third input group

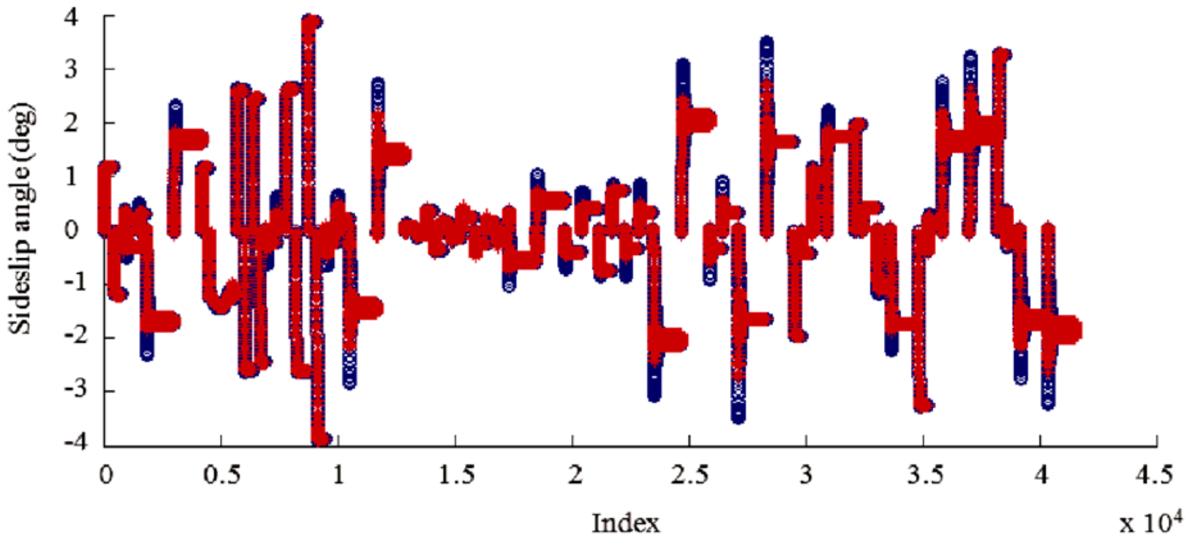


Figure 4. Training data for the first input group (the blue data represents the checking data and the red data represents the ANFIS estimated data)

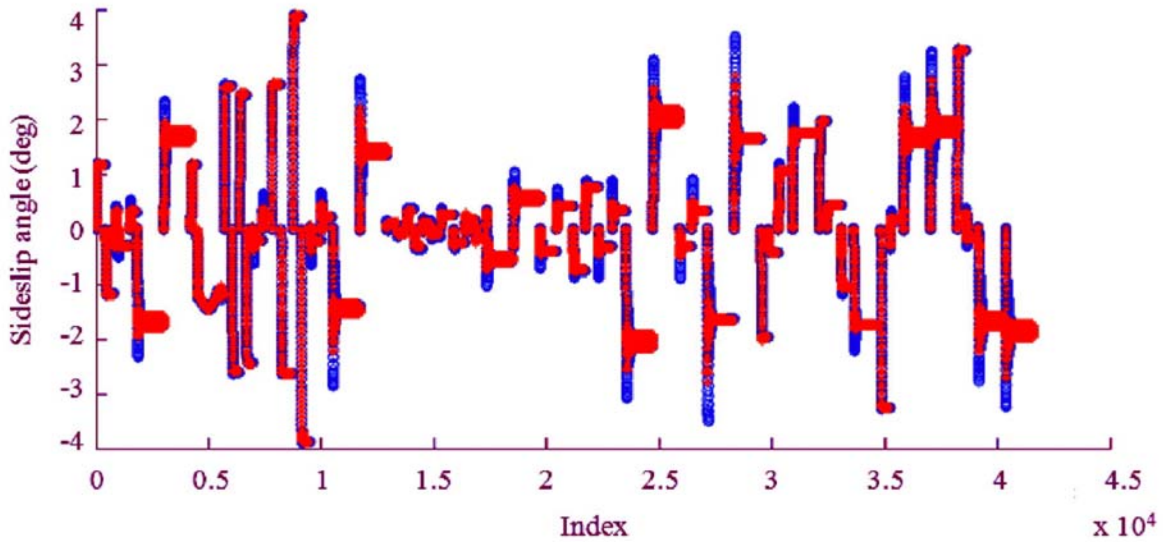


Figure 5. Training data for the second input group (the blue data represents the checking data and the red data represents the ANFIS estimated data)

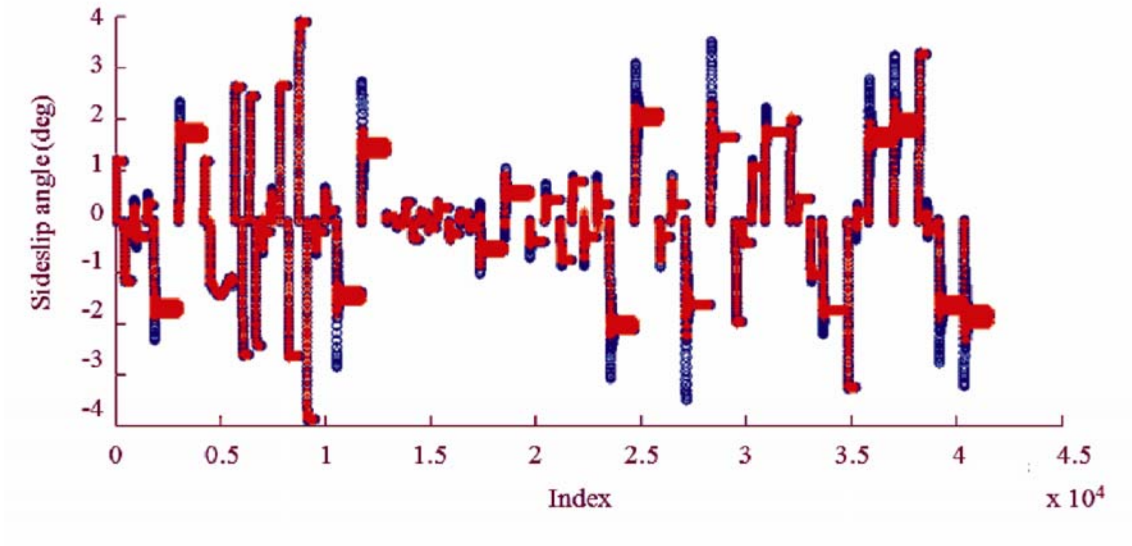


Figure 6. Training data for the third input group (the blue data represents the checking data and the red data represents the ANFIS estimated data)

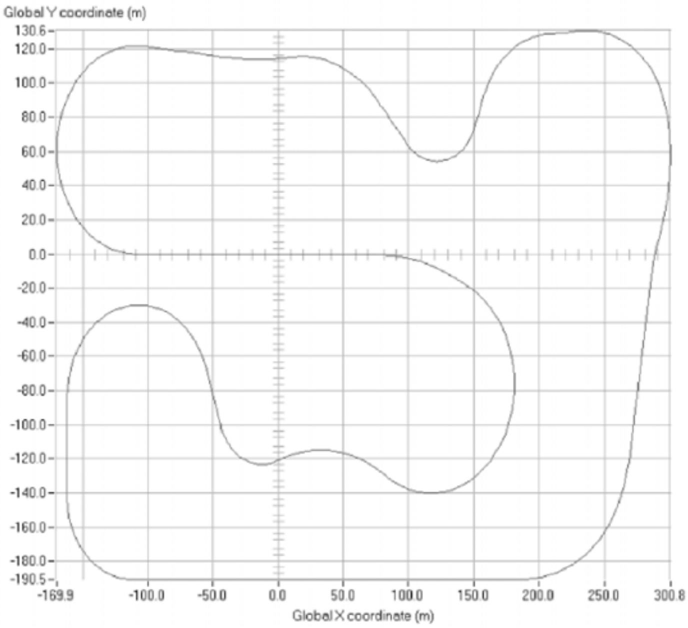


Figure 7. Road for testing

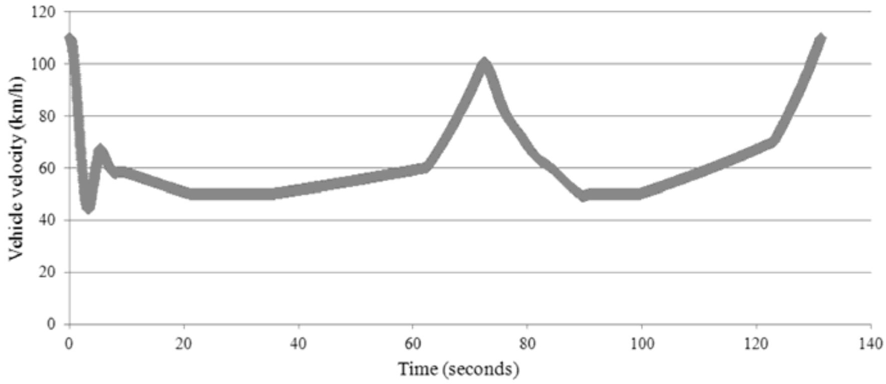


Figure 8. Vehicle velocity contour for testing

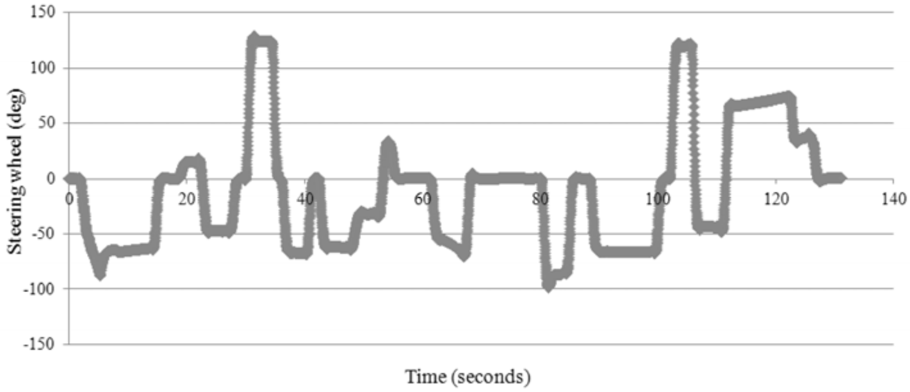


Figure 9. Steering wheel contour for testing

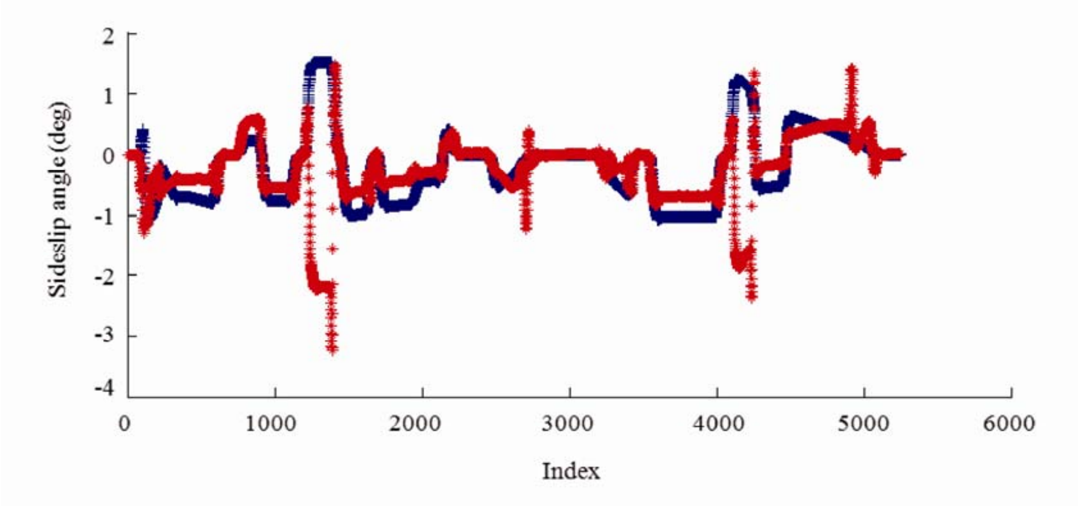


Figure 10. Checking data results for the first input group (the blue data represents the checking data and the red data represents the ANFIS estimated data)

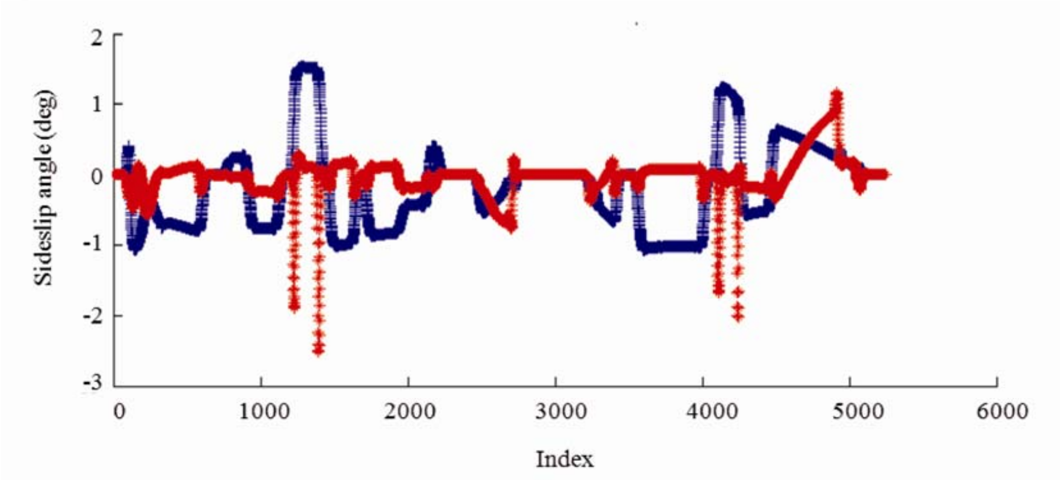


Figure 11. Checking data results for the second input group (the blue data represents the checking data and the red data represents the ANFIS estimated data)

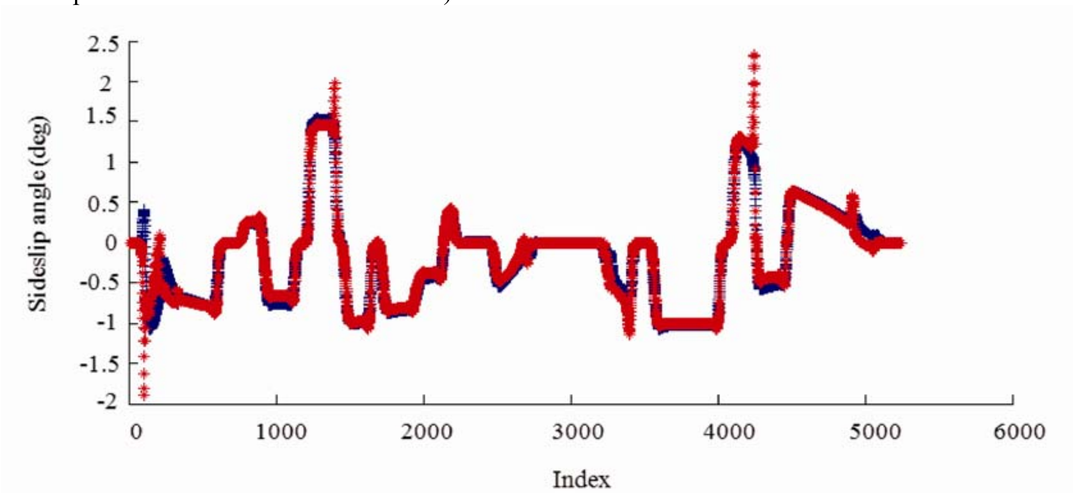


Figure 12. Checking data results for the third input group (the blue data represents the checking data and the red data represents the ANFIS estimated data)

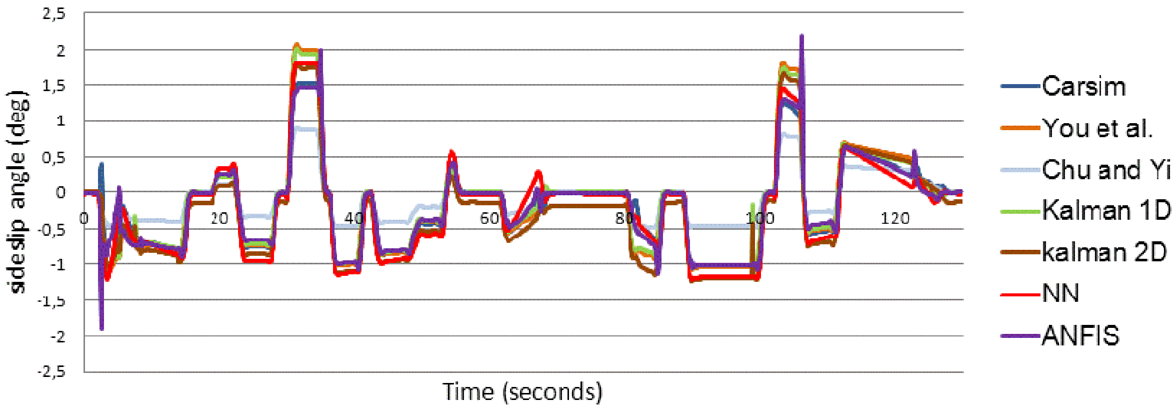


Figure 13. Comparison results for testing data among the proposed ANFIS-based sideslip angle estimator and common sideslip angle estimators

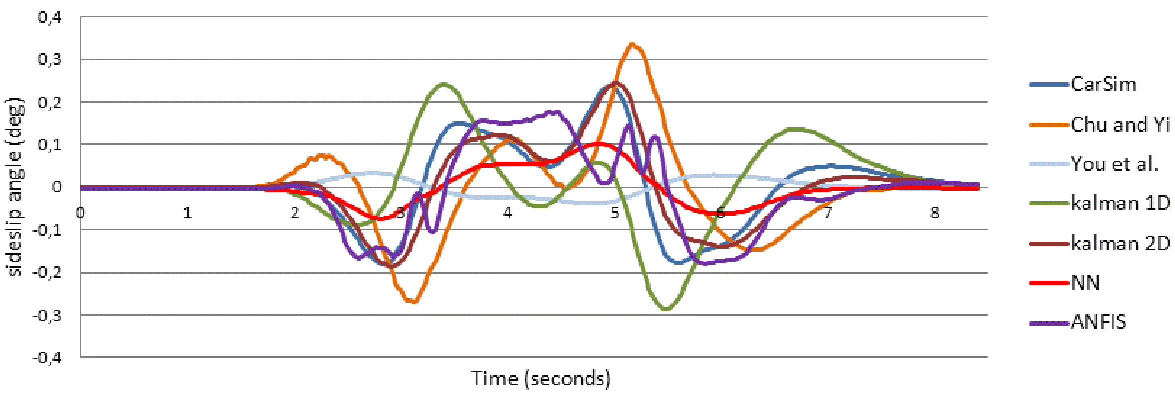


Figure 14. Comparison results for testing data among the proposed ANFIS-based sideslip angle estimator and common sideslip angle estimators for a lane change maneuver for a vehicle travelling at 90 km/h on a pavement of friction coefficient of 0.8

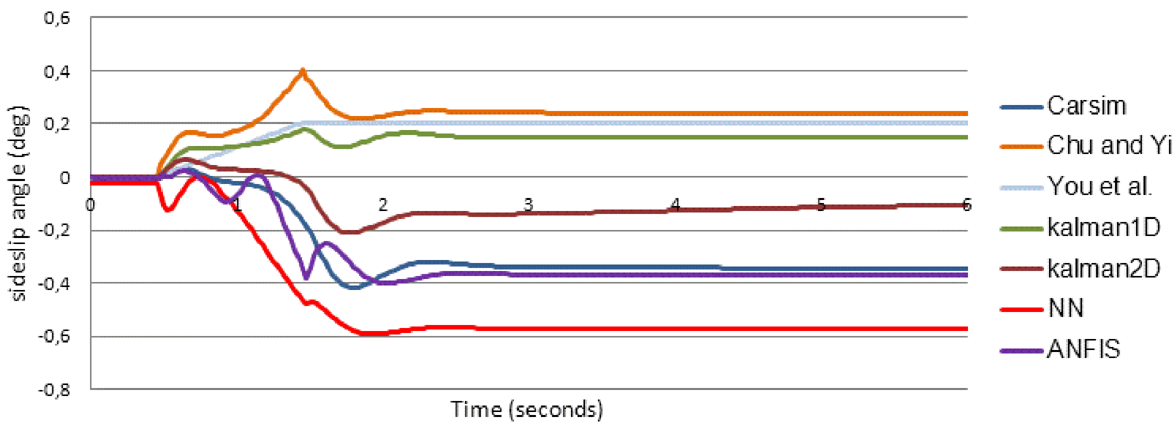


Figure 15. Results for a J-turn maneuver for a vehicle travelling at 80 km/h on a pavement of friction coefficient of 0.5

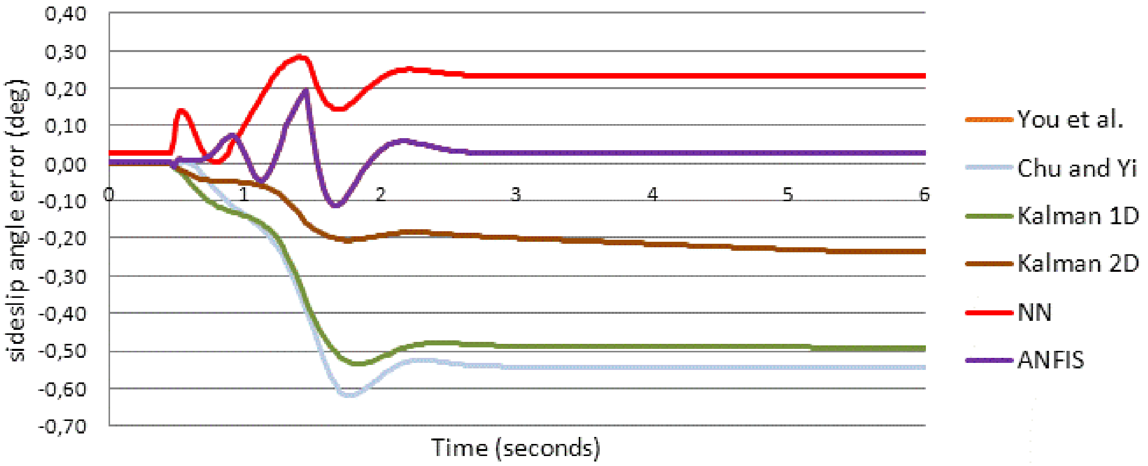


Figure 16. Comparison error results for testing data among the proposed ANFIS-based sideslip angle estimator and common sideslip angle estimators for a J-turn maneuver for a vehicle travelling at 80 km/h on a pavement of friction coefficient of 0.5