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Neural Network and IoT-based Test Maneuver Deployment for 2 DoF Vehicle Simulator

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***Abstract*— This paper presents the driving scenarios deployment for 2 DoF (Degree of Freedom) vehicle simulator based on IoT (Internet of Things) and Neural Network. The controller structure is chosen as Neural Network-based controller is preferred as the transferring appropriate accelerations in 3 axes in the 2 DoF manipulator evokes a non-linear problem. Due to the microcontroller used in the vehicle simulator to perform Neural Network calculations has limited processing capacity and speed, IoT-based computing and data transferring are chosen. Firstly, an open-loop measurement is performed to identify the vehicle simulator and to generate the training data for the neural network. Thereafter the acceleration data on the axes and the control signals are logged. Secondly, the neural network training is carried out with the logged data. Finally, the trained neural network was tested with various driving maneuvers. And the measurements are evaluated.**

Keywords- neural network; IoT; vehicle simulator; test maneuver; driving scenario.

I. INTRODUCTION

The vehicle simulators are mechatronic systems which provide the assessment of real vehicle behavior under a driving scenario or driving cycle [1]. In addition, the vehicle simulators are used for various purposes such as games and driver training. Besides, it can be transferred the real driving feeling to the driver through the simulator, to measure the driver's reactions realistically and to evaluate the driver's performance [2].

Basically, the vehicle simulators have a parallel manipulator structure. The Stewart platform is shown inFig. 1 as an example of parallel manipulators [3].

Vehicle simulators or parallel manipulators principally change the orientation of the platforms by the result of the sequential movements of linear actuators [4]. Here, in order to keep the platform in the desired orientation, feedback such as displacement, velocity, and acceleration information of the platform then the reference signals are generated over the controller [5].

The real driving feeling on the vehicle simulator can be achieved by transferring the reference accelerations of the linear actuators fed with the real driving information of the mobile platform on which the driver sits to the mobile platform. Therefore, the degree of freedom (DoF) over the connection points of the mobile platform and the number of actuators used can change [6].

Due to the fact that the accelerations in the x-y-z axes to be transferred to the mobile platform are transferred through different structural connections and the number of actuators leads to nonlinear controller requirements [7].

Neural network-based controller structures developed for nonlinear problems have come to the fore in the literature [8].

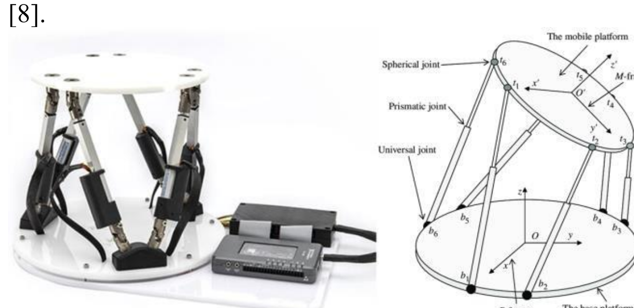


Figure 1. Stewart Platform [3].

It is seen that neural networks make important contributions to the solution of nonlinear problems with their features such as parameter fitting, classification, and estimation [9-13]. It is possible to create a real driving feeling on the driver's side with a neural network approach in which reference signals to be applied to linear actuators can be generated in the vehicle simulator by the acceleration information that should be on the x-y-z axes taken from the real driving data.

The Internet of Things (IoT) can make significant contributions to data transfer and processing. It is of great importance that the high processing power that may be needed during the processing of the signals coming from the sub-actuator or sensor units connected to a central processor and the derivation of the reference signals can be provided by the servers over the internet [14].

In this study, the data is transferred to the main server over an IoT, where linear actuators and acceleration information (IMU-Inertial Measurement Unit) are taken with the contributed point hardware-in-the-loop (HIL), is processed in the neural network and the necessary control signals are transferred to the vehicle simulator via IoT.

II. 2 DOF VEHICLE SIMULATOR

Here the 2 DoF vehicle simulator is dealt with. The design and prototype demonstration of the vehicle simulator is given in Fig. 2. The movement is provided via two linear actuators which are connected to the mobile platform as the driver's seat. The acceleration data on the x-y-z axes are received as feedback via the IMU. The control driver of the linear actuators and the IMU are transferred to the host computer via an IoT.

$$\tau = M(q)\ddot{q} + V(q,\dot{q}) + G(q) \tag{1}$$

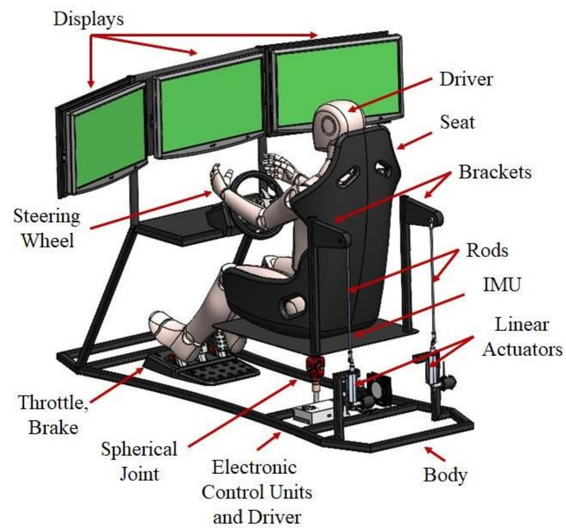
$$\frac{\mathrm{d}}{\mathrm{d}t}\left(\frac{\partial K}{\partial \dot{x}}\right) - \frac{\partial K}{\partial x} + \frac{\partial U}{\partial x} + \sum_{i=1}^{2} \varsigma_i G_{i1} = 0 \tag{2}$$

$$\frac{\mathrm{d}}{\mathrm{d}t}\left(\frac{\partial K}{\partial \dot{y}}\right) - \frac{\partial K}{\partial y} + \frac{\partial U}{\partial y} + \sum_{i=1}^{2} \varsigma_i G_{i2} = 0 \tag{3}$$

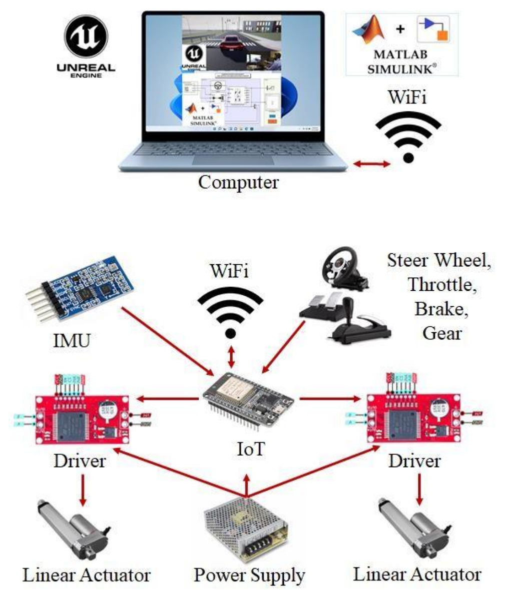
$$\tau_1 = \frac{d}{dt}\left(\frac{\partial \mathrm{K}}{\partial y_1}\right) - \frac{\partial \mathrm{K}}{\partial y_1} + \frac{\partial \mathrm{U}}{\partial y_1} + \sum_{i=1}^{2} \varsigma_i G_{i3} \tag{4}$$

$$\tau_2 = \frac{d}{dt}\left(\frac{\partial \mathrm{K}}{\partial y_2}\right) - \frac{\partial \mathrm{K}}{\partial y_2} + \frac{\partial \mathrm{U}}{\partial y_2} + \sum_{i=1}^{2} \varsigma_i G_{i4} \tag{5}$$

The mathematical model with an integrated kinematic and dynamic model for the 2 DoF vehicle simulator is represented between equation (1) and equation (5). Here, M(q) is the positional mass matrix, $V(q,\dot{q})$ is the vector of the nonlinear sets arising from the centripetal and Coriolis accelerations, and G(q) is the vector of the gravitational terms. K is the total kinetic energy of the system, U is the total potential energy of the system, G_{ij} is Lagrange multiplier [15-17].



(a) Vehicle Simulator 2 DoF CAD Model



(b) Hardware Architecture

(c) Vehicle Simulator Prototype

Figure 2. 2 DoF Vehicle Simulator.

III. MATERIALS AND METHOD

The process flow to be followed in this study is shown in Fig. 3. The process consists of 3 steps. In 1st step, the system identification and the generation of training data for the neural network are performed. For the system identification, the sinusoidal signals at different frequencies with 1,2,4,8,10,20 Hz, and 2 combinations of phase shift with 180 and 360 degrees are used. In 2nd step, training of the neural network model is carried out. The neural network structure is formed with 3 inputs (a_x, a_y, a_z) and 2 outputs (τ_1, τ_2). The neural network consists of two layers called as hidden and output. There are 60 neurons in the hidden layer and 2 neurons in the output layer. While tansig is used as the activation function in the hidden layer, purelin is used in the output layer. The data obtained for input and target in Step 1 are trained by using the Levenberg-Marquardt algorithm [9- 13]. In 3rd step, the trained neural network model with reference acceleration data derived from various test scenarios is tested. Here, the test scenarios contain the acceleration (a_x, a_y, a_z) data which are collected during the Double Lane Change (DLC), Constant Radius (CR), Fishhook (FH), Increase Steer (IST), Sine with Dwell (SwD) and Swept Sine (SS) tests [18].

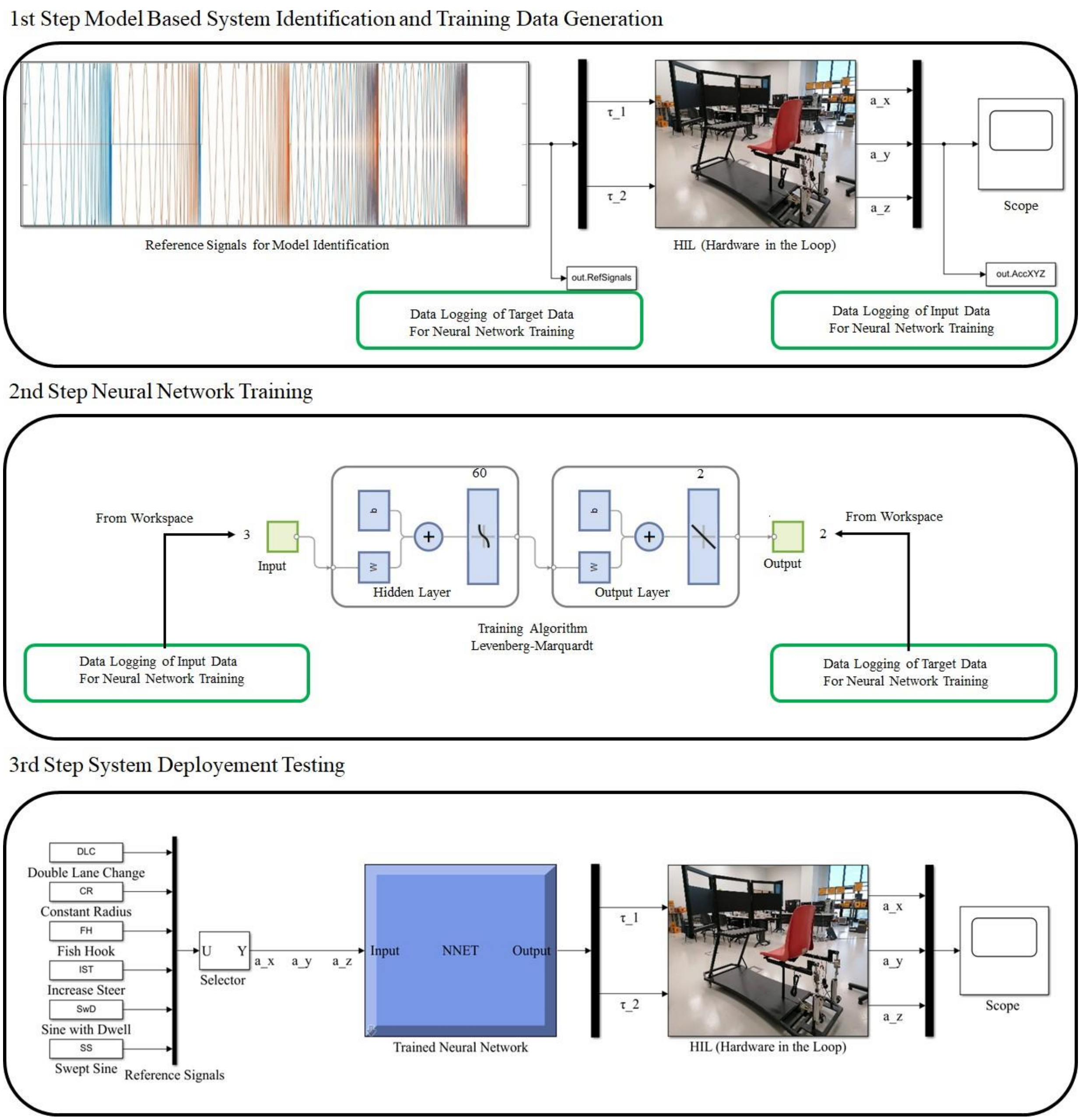


Figure 3. Methodology.

IV. RESULTS

The system identification signals used to define the vehicle simulator system and generate the input reference and target control signals for neural network training are given in Fig. 4. The acceleration (a_x, a_y, a_z) information measured by the IMU on the vehicle simulator during the signals in Fig. 4 applied to the vehicle simulator (HIL) is given in Fig. 5.

The neural network is trained with the data in Fig. 5 being input and the data in Fig. 4 being the target by the Levenberg-Marquardt algorithm. The training result shows the performance with 87.1% and MSE (Mean Squared Error) = 9.2.

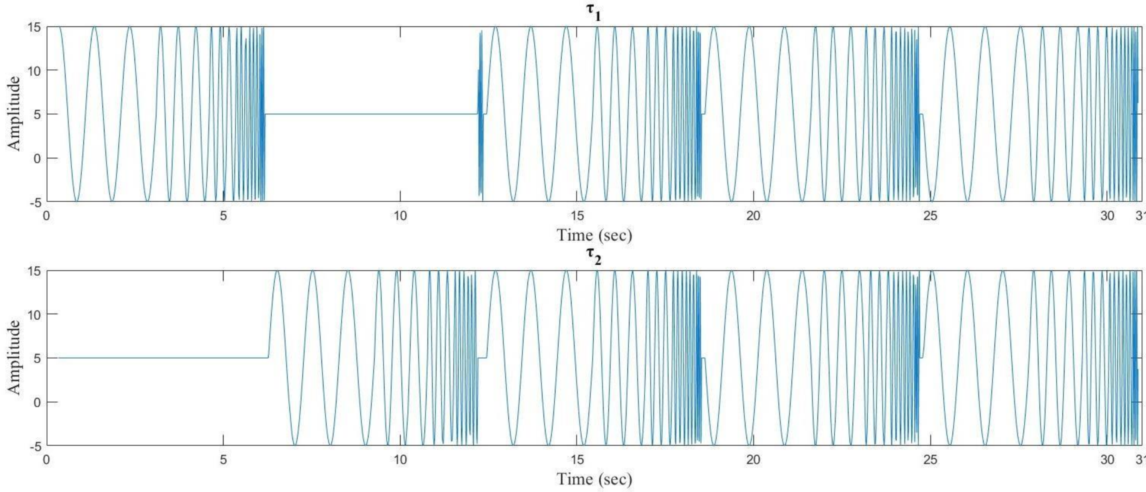


Figure 4. System Identification Inputs

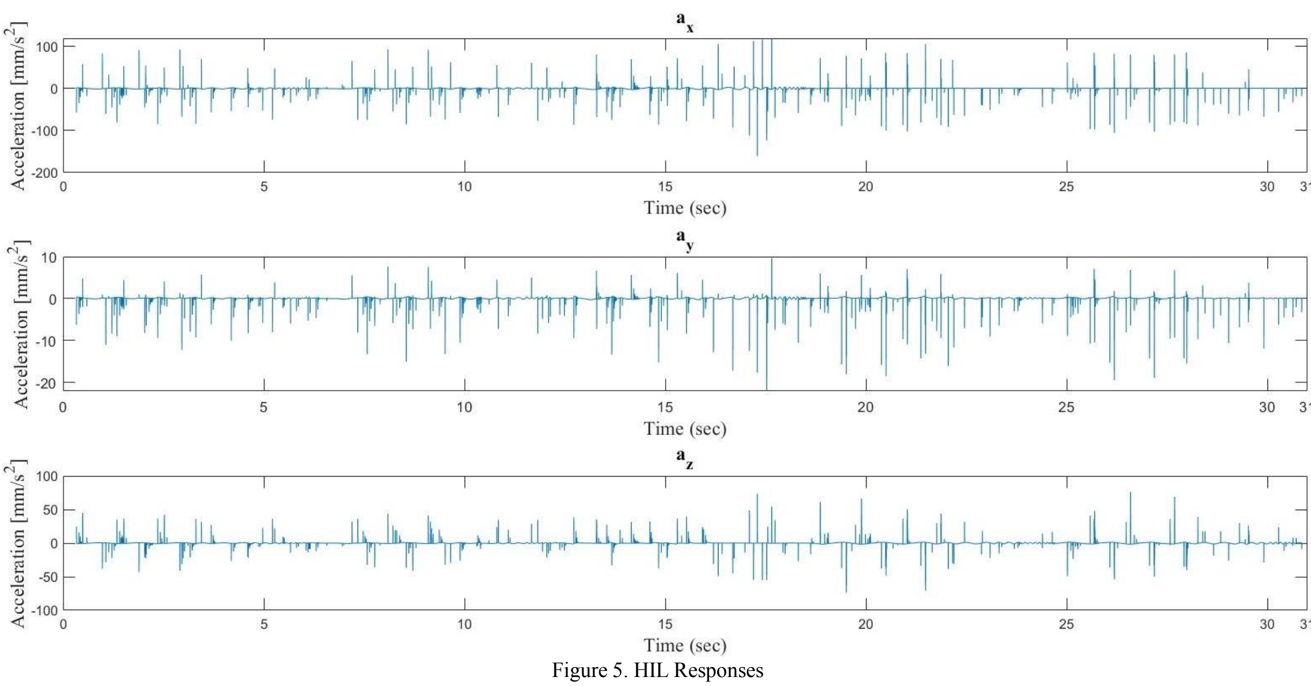


Figure 5. HIL Responses

The trained neural network is subjected to a validation process which is shown in Fig. 3 – in 3rd Step. Here the obtained acceleration data (a_x, a_y, a_z) from various test maneuvers are applied as the reference signal of the test cases for DLC, CR, IST, FH SwD and SS. While the reference test maneuvers are tested on a vehicle, the acceleration data are recorded as time series. The recorded test data is scaled according to the vehicle simulator constraints. The performance of the trained neural network is tried to be observed by applying the recorded acceleration data as time series to the neural network input separately for each test scenario. The applied reference signals during the tests and the obtained results are shown in Fig. 6.

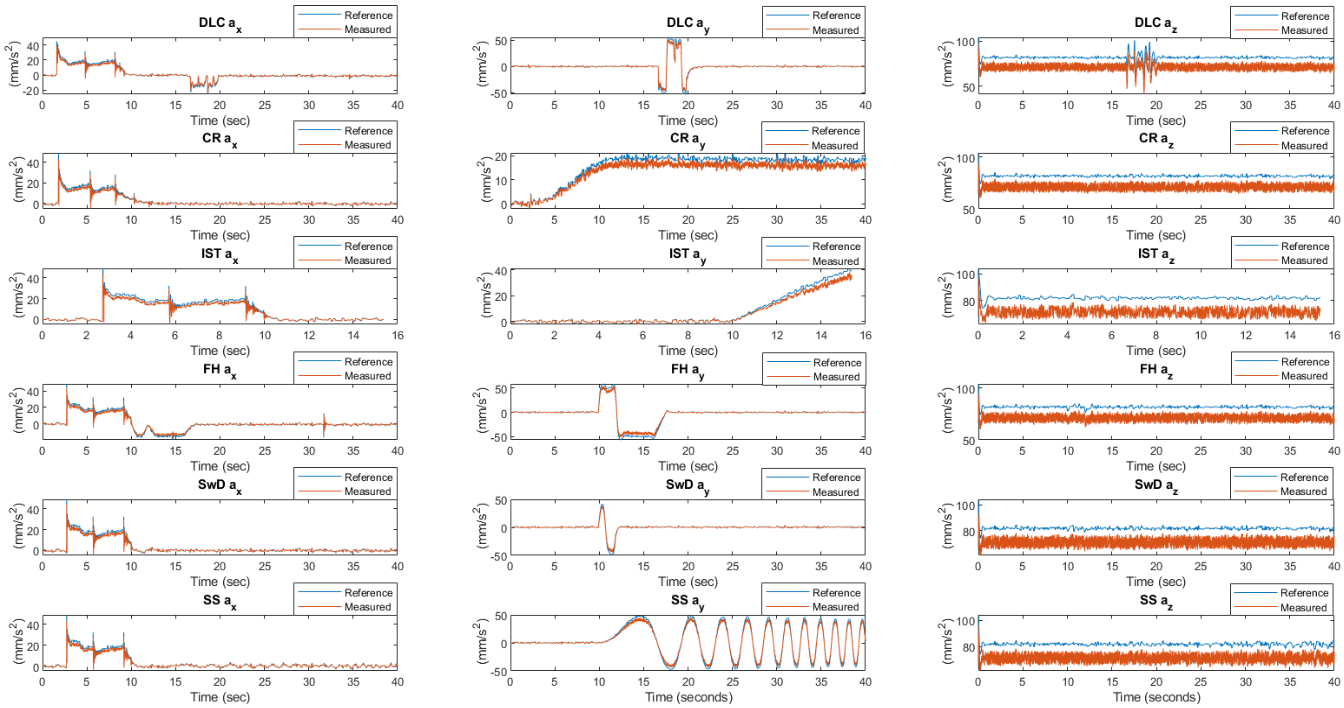


Figure 6. System Test Results, DLC (Double Lane Change), CR (Constant Radius), FH (Fishhook), IST (Increasing Steer), SwD (Sine with Dwell), SS (Swept Sine)

As the obtained results in Fig. 6 are considered as reference signals and measured signals, they are evaluated with mean absolute percentage error which is shown in Table I. As can be seen from Table I, the system verification is achieved with an average error of 13%.

Because the vehicle simulator used in this study has 2 DoF, it is seen that the acceleration error on the z-axis is relatively higher with respect to the acceleration errors on the x and y-axes. In addition, the minimum and maximum errors are observed as 7% and 19% respectively.

TABLE I. MAPE (MEAN ABSOLUTE PERCENTAGE ERROR) (%)

	a_x	a_y	a_z
DLC (Double Lane Change)	12.91%	13.00%	13.05%
CR (Constant Radius)	12.97%	13.00%	13.02%
IST (Increase Steer)	12.99%	12.97%	12.88%
FH (Fish Hook)	13.00%	13.11%	12.92%
SwD (Sine with Dwell)	12.96%	13.00%	13.05%
SS (Swept Sine)	12.95%	13.00%	13.00%

V. CONCLUSION

The vehicle simulator controlled via IoT is dealt with in this study. For various driving scenarios, the vehicle simulator needs to transfer the appropriate driving feeling to the driver. This process is achieved by transferring the acceleration of the axis set in accordance with the driving scenario of the relevant manipulators to the mobile platform.

In order to transfer the reference accelerations on 3 main axes to the driver over the controller, 2 linear actuators used on the 2 DoF vehicle simulators must be excited. Therefore, it is necessary to use a neural network-based controller for a nonlinear problem with 3 inputs and 2 outputs.

The neural network must be able to generate appropriate control signals by computation. The processing capacity of the microcontroller on the vehicle simulator reduces the driving feeling and causes delays in transferring the relevant accelerations to the driver. For this reason, the transferred data to the main server via IoT is processed in the neural network and the relevant reference signals are transferred to the actuators over the IoT to achieve a realistic driving feeling.

In IoT and neural network-based simulator, after the appropriate data acquisition for system identification and training of the neural network, the system is verified by testing with driving maneuvers such as DLC, CR, IST, FH, SwD and SS.

For training of the neural network, 2 combination signals at different frequencies with 1,2,4,8,10,20 Hz, and 2 combinations of phase shift with 180 and 360 degrees are applied to the vehicle simulator. Then the accelerations on the driver's seat are logged. The applied control signals are used as the target data of the neural network, and the acceleration data is used as the input data.

The neural network structure has 3 inputs, 2 outputs, and 2 layers. Tansig is preferred as the activation function with 60 neurons in the hidden layer of the neural network. In the output layer of the neural network, 2 neurons and purelin activation functions are preferred. With the logged data, the neural network is trained by the Levenberg-Marquardt training algorithm. After the training, the performance of the neural network is observed as 87.1% and MSE = 9.2%. As it is an acceptable performance, then the test phase is started.

The recorded acceleration data during driving maneuvers such as DLC, CR, IST, FH, SwD, and SS on the real vehicle are scaled according to the constraints of the driving simulator. Then, the processed acceleration data (ax, ay, az) for DLC, CR, IST, FH, SwD, and SS are applied to the input of the neural network, respectively, and the obtained control signals from the output of the neural network are transferred to the actuators of the vehicle simulators via IoT. The test process is completed by transferring the measured acceleration data from the IMU on the driver's seat to the main server via IoT.

After the test process, The MAPE results for the applied reference accelerations and the measured accelerations are summarized in Table 1. As can be seen from Table 1, the vehicle simulator can be tracking the reference accelerations with an average error of 13%. In addition, during the assessments, the maximum error for tracking the reference acceleration is 19%, and it was observed that results are acceptable for this type of system.

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