Designing neuro-fuzzy controller for electromagnetic anti-lock braking system (ABS) on electric vehicle

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Abstract. Anti-lock braking system (ABS) is used on vehicles to keep the wheels unlocked in sudden break (inside braking) and minimalize the stop distance of the vehicle. The problem of it when sudden break is the wheels locked so the vehicle steering couldn’t be controlled. The designed ABS system will be applied on ABS simulator using the electromagnetic braking. In normal condition or in condition without braking, longitudinal velocity of the vehicle will be equal with the velocity of wheel rotation, so the slip ratio will be 0 (0%) and if the velocity of wheel rotation is 0 (in locked condition) then the wheels will be slip 1 (100%). ABS system will keep the value of slip ratio so it will be 0.2 (20%). In this final assignment, the method that is used is Neuro-Fuzzy method to control the slip value on the wheels. The input is the expectable slip and the output is slip from plant. The learning algorithm which is used is Backpropagation that will work by feedforward to get actual output and work by feedback to get error value with target output. The network that was made based on fuzzy mechanism which are fuzzification, inference and defuzzification, Neuro-fuzzy controller can reduce overshoot plant respond to 43.2% compared to plant respond without controller by open loop.

1. Introduction
Braking is one of the most important part of the vehicle system. The correct way of braking is not doing an inside braking (sudden) because it can put the vehicle and other vehicles on the back in danger. But, if in emergency situation can block the speed of vehicle and put the driver in danger, then the driver should do the inside braking (sudden). In inside braking, wheels could lock so vehicle steering can not be controlled and this could cause the vehicle to slip. One of the system that can keep or control that brake is Anti-Lock Braking System (ABS). ABS system can control slip on vehicle’s wheels so the wheels couldn’t get locked when on brake. Slip on the wheels depends on the comparison between the difference of longitudinal velocity of the vehicle and the wheel speed with longitudinal velocity of the vehicle [1]. Electromagnetic braking is a braking system that is using an electromagnetic force to decelerate shaft motion of the vehicle. The electromagnetic braking that is used is microelectromagnetic clutch brake type, utilizing the electromagnetic field which is generated by coil because of the current going through the coil. The amount of magnetic field that is generated is directly proportional with the amount of current that is generated by coil. The force of magnetic field
that is generated is opposite with the direction of the wheel shaft rotation, so it can decelerate the velocity of vehicle.

A conventional controller, such as PID, cannot fulfill the need of ABS system because it couldn’t find the parameter of controller dynamically and couldn’t reduce the effect of disturbance of the system. Neuro-fuzzy controller is a smart control which is a combination of neural network algorithm and fuzzy control. Neural network algorithm is a supervised learning algorithm that is using neural network as a learning network. This network will be trained continuously by updating the value weighting on each neuron in hidden layer in feedforward and feedback.

2. System Description

2.1. Vehicle Dynamic [2]

The dynamic motion of a vehicle has 3 motion axes, they are longitudinal axis, vertical axis and transverse axis. Each of these axes has a rotation axis, they are roll, pitch and yaw. One of the force that works on the vehicle from starting to move until comes to a stop is a braking force that is in opposite direction with the direction of vehicle. When the braking force works, then the vehicle dynamic will change on 3 axes. In this discussion, the vehicle dynamic that will be discussed is on the longitudinal axis. On longitudinal axis, the braking effect will cause changes in 2 parameters, which are the velocity of vehicle’s longitudinal and the wheel rotation velocity. The rotation velocity and longitudinal velocity will be slip or brake slip. The slip value needs to be controlled in 15-30% so the vehicle can be driven in an inside brake (sudden) [6]. Slip happens in each wheel in a vehicle. The dynamic force that happens when there’s a braking on a wheel is the forces that work in the wheel. When braking, the working force is braking force, a normal vehicle force and road friction force. When the vehicle wheel locks (slip value 1) then the vehicle can’t be moved on lateral axis (axis transverse), so the vehicle can’t be moved either right or left to avoid an obstacle or an object that stands in front of the vehicle.

2.2. ABS Simulator [1]

ABS Simulator is a device that is used to test slip on a wheel without having to run the wheel on the road. On ABS simulator, the wheel will be installed on another wheel (tangent to each other) rotated with certain velocity. The velocity of the wheel will be represented by the upper wheel and the velocity of the bottom wheel will be represented by longitudinal velocity of the vehicle. ABS simulator only calculates longitudinal dynamic of the vehicle and not considering vertical dynamic and lateral (sides) of vehicle. The free wheel speed represents the car wheel speed ($\omega$) and the bottom wheel speed that is rotated by DC motor represents longitudinal velocity of the car ($v$). Figure 1 is block diagram of the ABS simulator system design that was made:
Based on figure 1, the ABS system itself consists of an expected slip as an input, computer as a controller block, Arduino Uno interface, ABS simulator and output in the form of a result calculation slip in Arduino Uno where the processed data was obtained from upper and bottom wheel speed sensor. ABS simulator plant is an upper wheel that is connected with an electromagnetic brake, and a bottom wheel that is connected with DC motor. Actuator on ABS simulator is an electromagnetic brake that managed the amount of brake presentation. The workflow of ABS system block diagram is the Arduino Uno will send the slip value through serial communication to computer, then the computer will process error signal using Neuro-fuzzy algorithm on Matlab program. The error signal process is ran by offline through general learning. After offline training has been conducted then the adjusted weight that has been obtained is inserted to the program by online stage. In online stage the error signal goes to the controller and generates control signal to ABS simulator plant through Arduino Uno as interface. ABS simulator design consist of hardware designing and software designing. Figure 2 shows the physical form of ABS simulator plant

3. System Designing

3.1. Plant Identification

Identification process aims to looking for parameter of a plant [3]. Parameter that has been obtained is used to make mathematical model from a plant by evaluating input output measuring data. Plant parameter identification is conducted dynamically by changing the bottom wheel velocity and pwm brake value of the upper wheel simultaneously. ABS plant parameter is a slip as output plant and the amount of pwm brake as input plant. The mathematical model of plant is calculated with stochastic approach structural model. Stochastic approach structural model that has been used is Auto Regressive Exogeneous structure (ARX).

Identification system process is conducted by getting slip data on several points of bottom wheel speed and several points of pwm brake value of upper wheel. The data acquisition was obtained by increasing the bottom wheel speed slowly and on each certain velocity was given a brake with several pwm value. The bottom wheel speed was increased every 10% pwm, so there are 10 points of velocity as a data sample. The bottom wheel speed was increased starts from 10% to 100%, so it was obtained the connection between the bottom wheel speed and the changing of duty cycle (PWM) of DC motor that was connected one shaft with bottom wheel as shown in Table 1 below:

| DC Motor PWM | Bottom Wheel Speed (RPM) |
|--------------|--------------------------|
| 10%          | 573                      |
| 20%          | 1224                     |
| 30%          | 1621                     |
| 40%          | 1854                     |
| 50%          | 1994                     |
| 60%          | 2097                     |
| 70%          | 2155                     |
| 80%          | 2173                     |
| 90%          | 2220                     |
| 100%         | 2313                     |

Every point of bottom wheel speed is given pwm brake from 0% to 100% (PWM brake is increased every 10%). When braking is conducted, then the bottom wheel has come to a stop, after that it can be ran again. The obtained data is a slip value on several velocity range of the bottom wheel and range of pwm brake value of the upper wheel. The work point of slip is the slip average that was
obtained on one point of working brake to one point of bottom wheel speed. The process data is slip data of bottom wheel speed and upper wheel speed when it starts to decelerate. When the pwm brake value is high, the upper part of the wheel had a chance to lock (not running) until the lower part of the wheel stops rotating. Here is the connection between the pwm brake changing of the upper wheel. Every point of bottom wheel speed is given 0% to 100% of pwm brake (PWM brake is increased every 10%). When braking is conducted, then the bottom wheel has come to a stop, after that it could be ran again. The obtained data is a slip value of several bottom wheel speed range and pwm brake value range of the upper wheel. Slip work point is the average of the obtained slip at one-point brake work to one-point bottom wheel speed. The processed data is slip data of the bottom wheel speed and upper wheel speed when it starts to decelerate. On the high pwm brake of the upper part of the wheel had a chance to lock (not rotating) until the lower part of the wheel stops rotating. Table 2 below is the connection between the changing of pwm brake on the upper wheel:

| Upper Wheel Pwm Brake | Bottom Wheel Speed (RPM) |
|-----------------------|--------------------------|
| 10%                   | 0.12934                  |
| 20%                   | 0.14616                  |
| 30%                   | 0.17498                  |
| 40%                   | 0.23304                  |
| 50%                   | 0.48866                  |
| 60%                   | 0.66523                  |
| 70%                   | 0.76070                  |
| 80%                   | 0.82027                  |
| 90%                   | 0.81499                  |
| 100%                  | 0.83794                  |

From the obtained data, it could be determined brake working point against slip for each bottom wheel speed as shown in Table 2, from the data in Table 2, its shown that working slip point has value more than 0.2 when pwm brake percentage is above 40% for 3 points of bottom wheel speed. In this final assignment, the author chose 100% (maximum) velocity for bottom wheel speed. Here is the graphic plot of the connection brake working point against slip for 100% pwm bottom wheel speed:

Based on figure3, the data of brake working point against slip, will be modeled plant model approach by stochastic approach structure which is Modeling with auto regressive exogenous (ARX)
using toolbox system identification Simulink. For choosing the model, na, nb and nk (delay) should be determined beforehand to determine the model order. Choosing model order based on the estimated error that was generated after putting in several model orders. There are 3 model orders in this process, they are model order 2, model order 3 and model order 4. Model order 3 which was obtained already represents the ABS plant mode. The value of RMSE from estimated error plant model is as big as or about 6.64% and the deviation standard value estimated error plant model is 0.0393. The obtained plant model is already in a district form with z domain:

\[
G(z) = \frac{0.0021184z^2}{z^3 - 1.9771z^2 + 0.97671z + 0.0024989}
\] (1)

After the plant model was obtained, next thing to do is to test plant model by open loop without controller to see the transient characteristic of system response. The given test signal is step unit signal of 0.2. This 0.2 value is the expectable slip value when the friction coefficient is on maximum on several road condition. In figure 4, there will be system response from test result by open loop:

3.2. Designing Neuro-Fuzzy Controller [4]

Neuro-fuzzy algorithm that is used is fuzzy modelling network algorithm (FMN). FMN has 3 different types, they are type I, type II and type III. FMN will identify the fuzzy rules and the membership function automatically by nerve network weights modification through backpropagation algorithm. In FMN type I using civil inference system, where the consequent of fuzzy inference system is a membership function. In FMN type II using civil inference system, where the consequent of fuzzy inference system is a single value (constant). In FMN type III using sugeno fuzzy inference system, where the consequent of fuzzy inference system using linear equation. In controller design using FMN type II to manage the slip value on ABS plant. The neuro-fuzzy algorithm calculation is divided into 2 stages, they are forward propagation stage and backpropagation stage. Figure 5 is an architecture of neuro-fuzzy network of FMN type II:

![Neuro-Fuzzy Network](image)

Figure 5 Neuro-Fuzzy Network [4].

![Block Diagram of General Learning](image)

Figure 6 Block Diagram of General Learning

Offline data training stages uses general learning and application stage or online stage. From the designed neuro-fuzzy model, general learning represents the invers dynamic of a plant. In offline stage, it is conducted data training to obtained minimum weight that is corresponding to the arc of neuro-fuzzy network by determine minimum error target and the amount of maximum iteration, as long as the error value is larger than the minimum error target, then iteration can still be proceeded. Figure 6 is block diagram of offline training using general learning.
Based on Figure 6, the target signal is the difference between control signal \((u(k))\) with estimated control signal \((U(k))\). For control signal value learning function could be a scalar value so the control signal value \((u(k))\) is a control signal value when the slip value is expected (set point). Based on the plant model in Figure 6, it is obtained the control signal value on this equation:

\[
X_d(k) = 0.2
\]

\[
u(k) = 0.345
\]

The signal training neuro-fuzzy offline data is conducted with maximum amount of iteration (maximum epoh) 100 and minimum error target \(10^{-6}\). In training data stage, the calculation of neuro-fuzzy consists of forward propagation and backpropagation. The error value in each iteration consists of forward propagation and backpropagation process will be squared then rooted. The error value in each iteration will always be compared with minimum error target until the error value is smaller than minimum error target.

The FMN type II network structure as shown in figure 7 consists of 7 layers. 7 layers of the network are one layer of input, 5 hidden layers and one layer of output. In this part, it will be explained that one of the stages from neuro-fuzzy algorithm calculation is forward propagation stage. Forward propagation stage works from layer A (input layer) to layer G (output layer). Table 3 below is the basic of fuzzy rules in the 6th layer:

| \(U\)   | \(\Delta Error\) |
|---------|-------------------|
|          | \(N\) \(Z\) \(P\) |
| \(Error\) | \(N\) \(N\) \(N\) | \(Z\) |
| \(Z\)    | \(N\) \(Z\) \(P\) |
| \(P\)    | \(Z\) \(P\) \(P\) |

Backpropagation stage will be conducted after forward propagation stage by revising the weight on neuro-fuzzy network. After the data training has been conducted by offline with forward propagation and backpropagation calculation stage with error target parameter \(10^{-6}\); learning rate 0.01; and maximum iteration (maximum epoh) is 100, then it is obtained the graph connection between the error value of each iteration (epoh) such as in figure 7 below:

![Figure 7 Training Result](image)

The stage after offline data training is online simulation stage. The corresponding weight will be obtained after the training process is finish with error minimum parameter \(10^{-6}\) and the amount of maximum iteration is 100. Training is finish when the error value has reached 0.000005094, although this value is still above \(10^{-6}\). But in this value, the error value is relatively not changing and not passing through \(10^{-6}\). So the iteration stops on the error value 0.000005094 on 100th iteration (epoh). So on...
100th epoch will be obtained the corresponding weights with the neuro-fuzzy network arc that will be the constant weight in online simulation stage. Table 4 below is the weight of training results:

| Weight   | Weight Value |
|----------|--------------|
| Wdcde1   | 0.0957       |
| Wdcde2   | 0.4736       |
| Week1    | 0.5462       |
| Week2    | 0.7070       |
| Wgde     | 0.0468       |
| Wgek     | 0.4276       |
| Wout     | [0.4895; 0.8396; 0.5820] |

After weight from neuro-fuzzy network arc has obtained then the next step is putting in those weight values to the neuro-fuzzy algorithm without backpropagation stage. Calculation stage that is used is only forward propagation stage.

4. Testing and Analysis

4.1. System Simulation

Simulation is conducted by testing the plant model by close loop against the set point in the form of signal step. Designing the neuro-fuzzy controller consists of 2 stages: offline data training and online data training. Plant model testing that will be analyzed is when the online stage which is the weights from offline training result has already put in to the neuro-fuzzy algorithm without backpropagation calculation. The given signal test is a step unit signal for 0.2 which represents the expectable slip value. In figure 8 will be shown a system response using neuro-fuzzy controller.

![Figure 8 ABS System Response using Neuro-Fuzzy Controller](image)

From the system response above in figure 8, it was obtained the transient response data and steady state system response will be shown in table 5 below:

| Rise Time | Settling time | Maximum Overshoot | ESS (%) |
|-----------|---------------|--------------------|---------|
| 4         | 8             | 6.8                | 0       |
System response with neuro-fuzzy controller that has been obtained will be compared with system response with PID controller as a comparison. The designed PID controller based on trial-error mechanism. The trial-error mechanism was conducted by tuning on Kp, Ki, and Kd parameters. In the first step, tuning was conducted by changing Kp parameter to be larger, then changing Ki parameter and Kd parameter. In figure 9 is system response comparison with PID controller and Neuro-Fuzzy controller using one of the tunings, which are Kp value tuned for 5, Ki value tuned for 4 and Kd value tuned for 4.

Response specification in table 6 will describe the tuning results for Kp, Ki and Kd which has been conducted against the transient system response:

| Kp | Ki | Kd | tr(second) | ts | Mp(%) | Ess(%) |
|----|----|----|------------|----|-------|--------|
| 5  | 3  | 4  | 1.56       | 8  | 11.25 | 0      |
| 5  | 4  | 4  | 1.35       | 8.5| 16.1  | 0      |
| 5  | 4  | 3  | 1.11       | 5.76| 13.15 | 0      |
| 5  | 3  | 4  | 1.29       | 8.25| 8.25  | 0      |
| 5  | 3  | 1  | 0.6        | 6.2 | 23.5  | 0      |

Based on table 6, the average rise time of PID controller is much better compares to the rise time of neuro-fuzzy controller which means the neuro-fuzzy controller is not capable to give a better rise time compared to PID controller. Neuro-fuzzy controller is capable to give settling time value twice larger for system response without controller. Neuro-fuzzy controller has settling time value that doesn’t have much difference with several PID controller parameter tuning results, which means the neuro-fuzzy controller generally is more capable to give much better settling time value compared to PID controller. Neuro-fuzzy controller is capable on reducing the overshoot in system response without controller for 43.2%, which means the neuro-fuzzy controller is capable to reduce the overshoot in system response significantly. Neuro-fuzzy controller also has a smaller overshoot value compared to PID controller. Neuro-fuzzy and PID controller can fix the system because they have steady state error approaching 0%.

4.2. Implementation Result

Implementation is conducted on ABS real plant simulator with Matlab software. The implementation result for 2300 rpm velocity (100%) is shown in figure 10.
Based on ABS system response on figure 10 shows that neuro-fuzzy controller can work in a braking condition. When on braking the slip value can’t follow the reference signal value for 0.2 but it can keep the upper wheel not to lock or keeping the slip value not 1. From system response on figure 10 has rise time value for 0.2 seconds and error steady state for 50%. When the braking is conducted, there is a longitudinal velocity and rotation speed change as an effect from the controllable slip value. Here is the velocity response when the neuro-fuzzy controller works, which will be shown in figure 11.

The reduction of longitudinal velocity and rotation speed also have flatter slope compared to the reduction of velocity without ABS system. The implementation also conducted in 2200 rpm velocity (90%). In 2200 rpm velocity, slip value that is generated can follow the reference signal for 0.2. Figure 12 below is ABS system response in 2200 rpm velocity:

Based on figure 12, the ABS system response can follow reference signal for 0.2 when braking is conducted. But it has a steady state error value (ess) which tends to increase until the upper wheel and the bottom wheel stop. Neuro-fuzzy controller can work for 2200 rpm velocity because it can keep the upper wheel stays unlock when the braking is conducted. The system response is 1 when the upper and bottom wheel has already stopped, it’s because of the effect of slip calculation which has 0/0 value when the upper and bottom wheel has stopped.
5. Conclusion

Based on plant model test result using neuro-fuzzy controller by simulation and implementation result on ABS real plant using neuro-fuzzy controller, it can be concluded to several points, which are:

- Neuro-fuzzy controller can reduce the overshoot system response for 43.2% and accelerate the time response twice faster to reach stable condition.
- The designed neuro-fuzzy controller can work when the implementation for bottom wheel speed is 2200 and 2300 rpm.
- For 2300 rpm wheel speed, the neuro-fuzzy controller has an error steady state value (ess) for 50% and rise time for 0.2 seconds. Slip value that is generated is still in an acceptable range in some road conditions, which is 0.15-0.3 [6]. For 2200 rpm velocity can follow signal reference approximately 0.2 for 0.5 second in initial braking.

6. References

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