International Journal of Technology and Emerging Sciences (IJTES)

www.mapscipub.com

Volume 03 || Issue 01 || January 2023 || pp. 01-06 E-ISSN: 2583-1925

Reinforcement Learning for Electric Vehicles Suspension System

Akash Anant Veer[1], H. P. Khairnar[2]

[1]*MTech Student, Department of Mechanical Engineering, VJTI, Mumbai, Maharashtra, India*
[2]*Assistant Professor, Department of Mechanical Engineering, VJTI, Mumbai, Maharashtra, India*

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Abstract – *Vibration control of an Electric Vehicle is a complex process. Due to changed dynamics of EV the before used suspension needs to be upgraded according to the new weight distribution and added vibrations from the electric motor. This research deals with the mentioned problem of additional vibrations inclusion to the system. A Quarter car model of an Electric Vehicle is designed on MATLAB / Simulink that consisted of Spring mass damper system along with an electric motor mounted on the unsprung mass. This electric motor adds Rotary vibrations to the system. Road disturbances of Road roughness Class B are applied to test the model. A Hydraulic Actuator is used to simulate an Active Suspension for the EV. This Hydraulic Actuator is controlled by PID controller and also simulated to be controlled by Reinforcement Learning Controller. The parameters used for both the types of controllers are same. Firstly, the PID controller is used to test the simulation so changes in the system due to electric motor addition are confirmed. Then the Reinforcement Controller is used to optimize the system. Results obtained showed reduction of Sprung mass displacement by 25.46 % and Sprung mass acceleration by 15.97 % for RL Controller as compared to PID Controller.*

Key Words: **Reinforcement Learning, PID Controller, Electric Vehicle, Electric Motor, Hydraulic Actuator, MATLAB, Simulink, Active Suspension System**

1. INTRODUCTION

Vibrations caused due to uneven road conditions and now added electric motor vibrations on the Electric vehicle body and passengers are isolated by Suspension System. An Active type suspension uses an on-board controller which collects data from sensors and processes it to control the actuator that ensures the required vehicle stability and passenger comfort. With the adaption of EV's the IC Engines are replaced by Electric motors which added rotational type vibrations on the vehicles unsprung mass. In [1] Shuting Huang showed the influence of changed dynamic parameters on the ride comfort of EV as compared to traditional vehicle. Thus, to improve the fallen ride comfort of EV correction values are required for Stiffness, Damping coefficient and mass distribution. As said above this research is only limited to adaption of a better controller system for Active Suspension. Various Active Suspension methods such as PID controller, Fuzzy Logic controller, Predictive controller, Adaptive controller, Neural Network controller and many more have to be used before. A lot of them showed good outcomes for changed dynamic behavior but still better could be done. A PID type controller is widely used in industries which have shown decent results but it has its own limitations. Suspension system works in a dynamic environment that deals with non-linear equations for which PID is not really suited. It shows low performance in handling systems with strong non-linearity. Actuator have to be worked at shorter time period thus multiple constraints are difficult to handle. PID shows poor control performance for an integrated process and a large time delay.

All these limitations have to be overcome to make the system faster and smoother in operation. Machine Learning is a type of Artificial Intelligence which predicts the future possibilities based on its past experiences. Such system controllers can be used in a dynamic environment for controlling vehicles suspension system. Pattern Identification and huge data accumulation which could not have been possible using other controllers can be easily done with excellence by ML. Reinforcement Learning which is a sub type of ML is used to teach the system to complete a multi-step process whose rules are already predefined by the users. It works on a reward feedback system to work but moreover it teaches itself to complete the given task. RL adapts to new environment easily. As compared to other control systems a large number of real time data can be managed by RL. Also, Ratnakar et al. [6] have performed simulation on performance of leaf spring on heavy and light vehicles.

Nomenclature

$\mathbf{m_1}$, $\mathbf{m_2}$, $\mathbf{m_m}$	Sprung, Unsprung and Electric Motor mass
$\mathbf{k_1}$, $\mathbf{k_t}$, $\mathbf{k_m}$	Stiffness of Spring, Tire and Motor
$\mathbf{c_1}$, $\mathbf{c_t}$, $\mathbf{c_m}$	Damping coefficient of Damper, Tire and Motor

1.1 Modelling

A quarter car model is designed on Matlab Simulink. It consists of a spring mass damper system. The model consists of external road disturbances along with electric motor excitations. Sprung mass $\mathbf{m_1}$ is suspended by a Spring Damper system of Stiffness $\mathbf{k_1}$ and Damping coefficient $\mathbf{c_1}$. Unsprung mass $\mathbf{m_2}$ is directly on Tire with Stiffness $\mathbf{k_t}$ and Damping coefficient $\mathbf{c_t}$. Electric motor of mass $\mathbf{m_m}$ is mounted on Unsprung mass with its own stiffness $\mathbf{k_m}$ and damping coefficient c_m. While z_1, z_2 and z_m represents displacements of Sprung mass, Unsprung mass and Electric motor. Along with that an Actuator is also applying force F_A on both the masses.

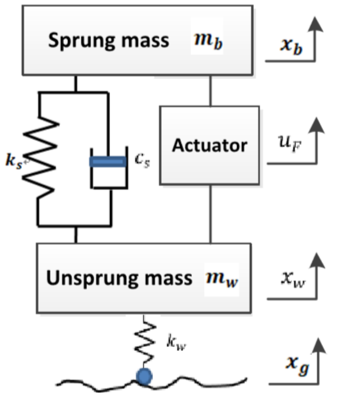

Figure – 1: Quarter Car Model [2]

Dynamic equations of the suspension system are as follows:

$$\ddot{z_1} = \frac{1}{m_1}[\,k_1\,(z_2 - z_1) + c_1\,(\dot{z_2} - \dot{z_1}) + F_A] \cdots\cdots\cdots (1)$$

$$\ddot{z_m} = \frac{1}{m_m}[k_m(z_2 - z_m) + c_m(\dot{z_2} - \dot{z_1}) + F_m] \cdots\cdots\cdots (2)$$

$$\ddot{z_2} = \frac{1}{m_2}[k_1(z_1 - z_2) + c_1(\dot{z_1} - \dot{z_2}) + k_m(z_m - z_2) +$$

$$c_m(\dot{z_m} - \dot{z_2}) + k_t(q - z_2) + c_t(\dot{q} - \dot{z_2}) - F_A] \cdots\cdots\cdots (3)$$

Road excitation from **q(t)** is fed to the simulation. The road profile used is derived from the following equation:

$$\dot{q}(t) = -2\pi v n_{00} q(t) + 2\pi n_0 \sqrt{v G_q(n_0)} * \omega(t) \cdots\cdots\cdots (4)$$

Were,

$$n_0 = 0.1$$

$$n_{00} = 0.011$$

$$v = 50\frac{km}{hr} = 13.8889\frac{m}{s}$$

Table – 1: Road Roughness [3]

Road Class	$G_q(n_0)10^{-6}\ m^3$
A	16
B	64
C	256
D	1024
E	4096
F	16384

Road roughness of Class B is considered for this research work.

Motor Excitation force F_m is derived from [1] as equation (5) and is shown in below figure.

$$F_m = m_s e \omega_r^2 \cos(\omega_r t) \cdots\cdots\cdots (5)$$

$$= 1500\cos(1000t)$$

Were,

$$m_s = Motor\ Stator\ Mass$$

$$m_s = 60kg$$

$$e = 0.527 * 10^{-3} m$$

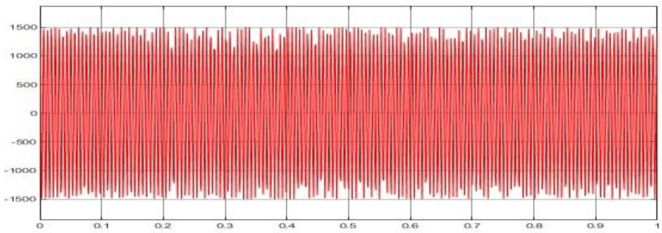

Figure – 2: Motor Excitation Force for 1 sec

The Active suspension for the model has a Hydraulic actuator. From [4] the equations for Hydraulic actuator are derived as follows:

$$\dot{f} = -\alpha A_P^2(\dot{z_s} - \dot{z_u}) - \beta f + \gamma A_p x_{sp} \sqrt{\frac{P_s - sgn(x_{sp})f}{A_p}} \cdots (6)$$

$$\dot{x_{sp}} = \frac{1}{\tau}(-x_{sp} + K_{sv} i_{sv}) \cdots\cdots\cdots (7)$$

Were,

$$f = Actuating\ Force$$

$$x_{sp} = Spool\ Displacement$$

$$\beta = \text{Bulk Modulus}$$

$$P_s = Supply\ Pressure$$

$$A_p = Hydraulic\ Piston\ Area$$

$$i_{sv} = \text{Servo Valve Current Input}$$

$$K_{sv} = \text{Valve gain} = 1\ (\text{Assumed})$$

Now simplifying above equations, we obtain equations (8), (9) and (10)

$$\alpha = \frac{4\beta}{V_t} \cdots\cdots\cdots (8)$$

$$\beta = \alpha C_{tp} \cdots\cdots\cdots (9)$$

$$\gamma = \alpha C_d w \sqrt{\frac{1}{\rho}} \cdots\cdots\cdots (10)$$

Were,

$$V_t = \text{Total Volume of Actuating Cylinder Chamber}$$

$$C_{tp} = \text{Leakage Coefficient}$$

$$C_d = \text{Discharge Coefficient}$$

$$\mathbf{w = Spool\ Valve\ Gradient}$$

$$\mathbf{\rho = Hydraulic\ Oil\ Density}$$

For further simplification we convert above equations into (11), (12) and (13) we get,

$$\mathbf{g} = \frac{\boldsymbol{\alpha} \mathbf{A_p}(\dot{\mathbf{z}}_\mathbf{s} - \dot{\mathbf{z}}_\mathbf{4}) + \boldsymbol{\beta} \mathbf{P_L}}{\boldsymbol{\gamma}\sqrt{\mathbf{P_s} - \mathbf{sgn}(\mathbf{x_{sp}})\mathbf{P_L}}} \cdots\cdots\cdots (\mathbf{11})$$

$$\mathbf{h} = \frac{\mathbf{1}}{\boldsymbol{\gamma}\mathbf{A_p}\sqrt{\mathbf{P_s} - \mathbf{sgn}(\mathbf{x_{sp}})\mathbf{P_L}}} \cdots\cdots\cdots (\mathbf{12})$$

$$\mathbf{P_L} = \frac{\mathbf{f}}{\mathbf{A_p}} \cdots\cdots\cdots (\mathbf{13})$$

Substituting equations (11), (12) and (13) in equations (6) we get our final equation (14) that represents Hydraulic Actuating Force.

$$\dot{\mathbf{f}} = \left[\frac{\mathbf{1}}{\mathbf{h}}(\mathbf{f} - \mathbf{g})\right] \cdots\cdots\cdots (\mathbf{14})$$

Table – 2: Hydraulic Actuator Parameters [3]

Parameters	Value
$\boldsymbol{\tau}$	$\frac{\mathbf{1}}{\mathbf{30}}$
$\boldsymbol{\beta}$	$\mathbf{1}$
$\mathbf{A_p}$	$\mathbf{3.35 * 10^{-4}}$
$\mathbf{P_s}$	$\mathbf{10342500\ N/}\boldsymbol{m}^\mathbf{2}$
$\boldsymbol{\alpha}$	$\mathbf{4.515 * 10^{13}}$
$\boldsymbol{\gamma}$	$\mathbf{1.545 * 10^{9}}$

Thus, finally a complete Quarter car model of Active Suspension consisting of Spring Mass damper along with a Hydraulic actuator, road disturbances and Electric Motor excitation forces is completed.

1.1.1 PID Controller

A PID controller is used with following specifications taken from [5]

Relative Error of 0 is compared to Sprung mass displacement.

Were,

$$\mathbf{K_p = 3055}$$

$$\mathbf{K_d = 32060}$$

$$\mathbf{K_i = 0.7}$$

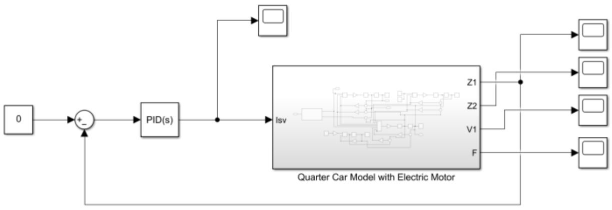

Figure – 3: Quarter car model with PID controller

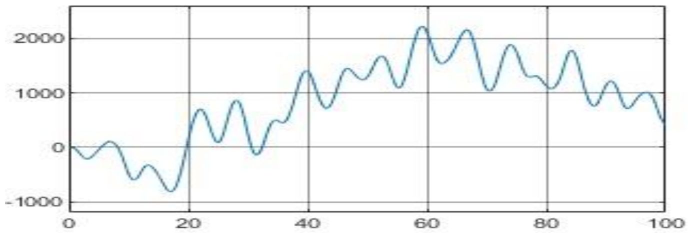

Figure – 4: PID Action

Above Figure 4 shows the PID input to the Servo Valve of the Hydraulic Actuator. The input signal is in terms of Voltage to the servo valve. The PID takes feedback from the system then cross checks it with the reference value (here Ref = 0) and then gives an appropriate input to the System.

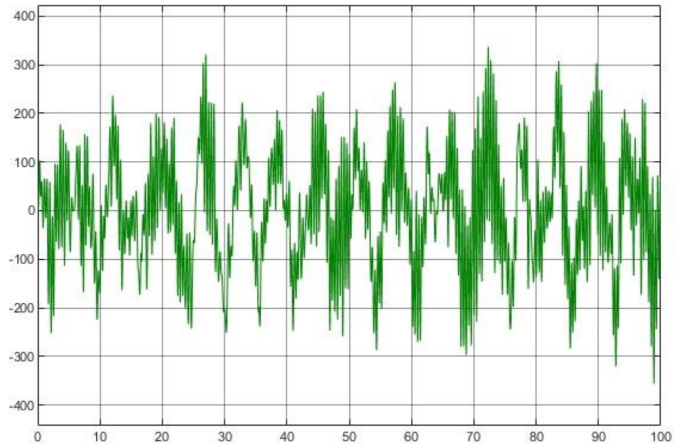

Figure – 5: PID Hydraulic Actuator Force

In Figure 5 we can see the action of Hydraulic Actuator Force on the suspension system. This is in terms of Newton (N). The PID input to servo valve takes the further action to move the actuator arm accordingly.

1.1.2 RL Controller

RL model is now setup for same working environment conditions as of for PID controller. RLDDPG agent is chosen as Actor agent. The reward signal used is referred from [2] and is shown in below equation (15).

$$\mathbf{r} = -\mathbf{1000}(\dot{\mathbf{z}}_\mathbf{1})^\mathbf{2} + \mathbf{0.1}(|\mathbf{u}|) + (\mathbf{5\ if\ z_1 = 0}) \cdots\cdots\cdots (\mathbf{15})$$

The simulation is considered completed at Sprung mass displacement value as mentioned below.

$$z_1 = 0.000015\ \mathrm{m}$$

The controller takes in observations from Sprung mass displacement and acceleration.

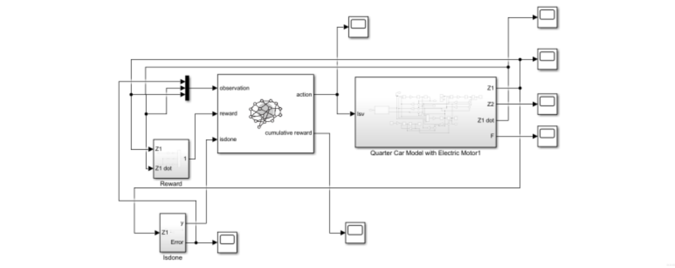

Figure – 6: Quarter car model with RL controller

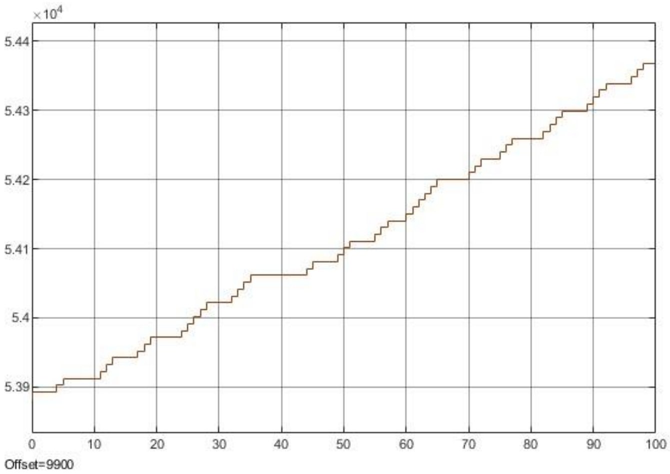

Figure – 7: RL Cumulative Reward

Reward generation is one of the key elements of a RL controller. The reward signal designed for our system is shown in equation (15). Figure 7 represents the Cumulative Reward generated by the controller while taking action on the system.

Is Done: The simulation is considered completed at Sprung mass displacement value as mentioned below.

$$z_1 = 0.000015\ \mathrm{m}$$

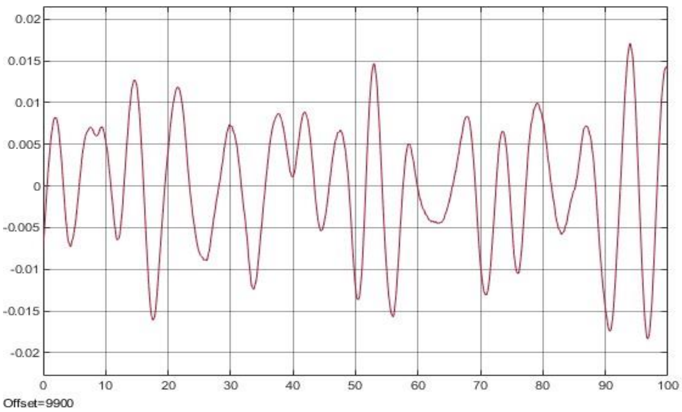

Figure – 8: RL Error

Above Figure 8 shows us the error generated by the RL controller. This error is the difference between the Set Reference Value and the Input Sprung Mass Displacement. Error helps the controller to define weather an action is complete or not.

Observations: The controller takes in observations from Sprung mass displacement and acceleration as a Vector input.

Action: The agent gives action to the designed system in terms of Servo Valve Input Current for the Hydraulic Actuator.

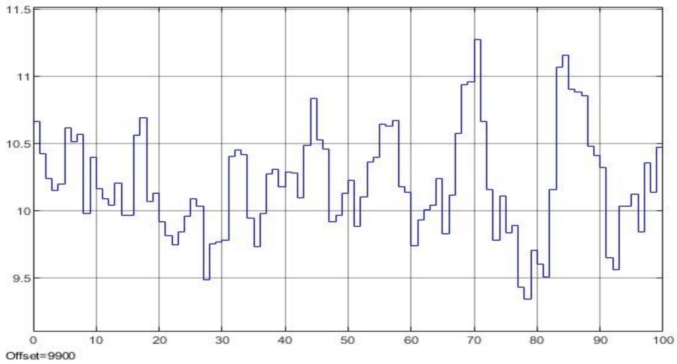

Figure – 9: RL Action Input

Similar to PID controller, Figure 9 represents the RL Action Input to the Servo Valve of the Hydraulic Actuator. Here also feedback is taken from the system in terms of the Sprung mass displacement. This displacement is compared to a set reference value of 0.000015m.

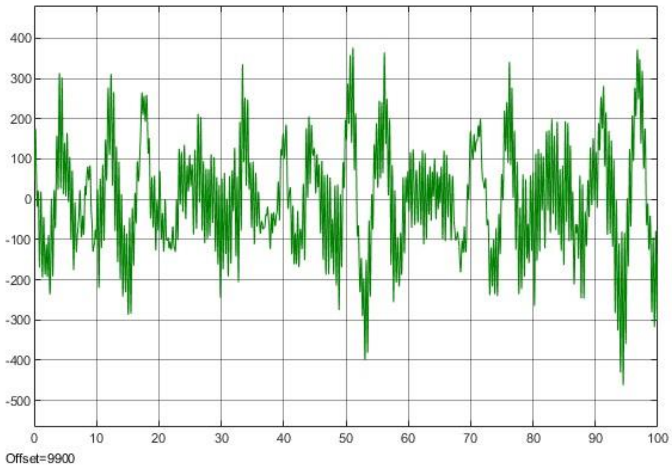

Figure – 10: RL Hydraulic Actuator Force

Figure 10 represents the Hydraulic Actuator Force to the system. This force in Newtons (N) provides the excess displacement required by the suspension to raise or lower the system.

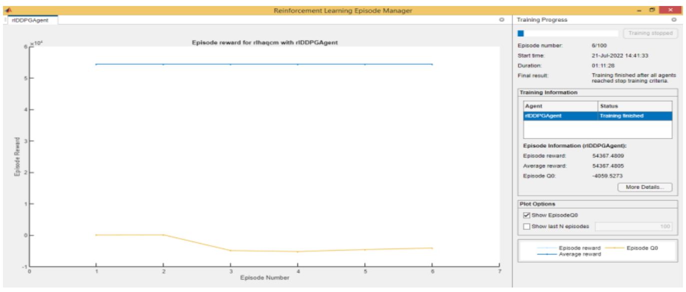

Figure – 11: Reinforcement Learning Episode Manager

Figure 11 shows the Reinforcement Learning Episode Manager of MATLAB. This shows us the variation of rewards according to the episodes the RL agent runs while training it.

3. RESULTS

3.1 PID Results

The results obtained for PID controller are shown below:

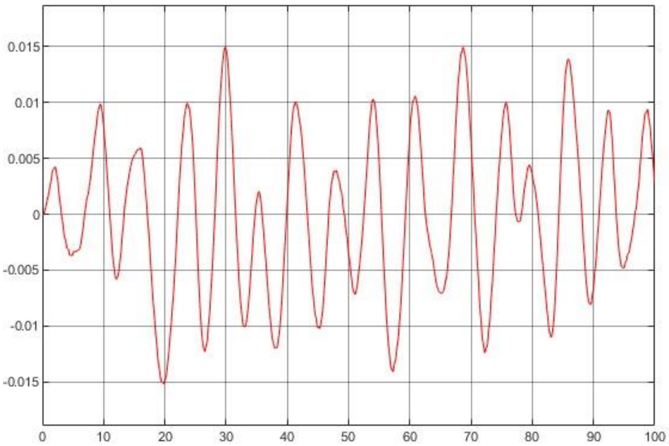

Figure – 12: Sprung Mass Displacement for PID

Figure 12 shows the Sprung mass displacement by the PID controller in terms of displacement in meters (m) on Y-axis and time in seconds (s) on X-axis. The maximum displacement within this 100 s simulation was seen to be close to 0.015 m.

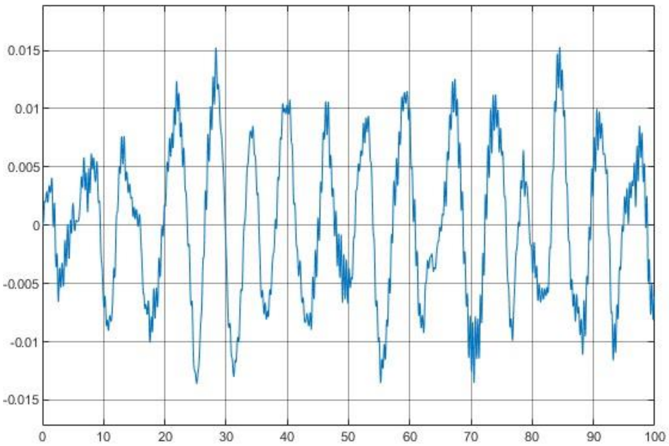

Figure – 13: Sprung Mass Acceleration for PID

Figure 13 represents the Acceleration of the Sprung mass for PID controller. On Y-aixs acceleration in meters per second (m/s) is shown and time (s) on X-axis.

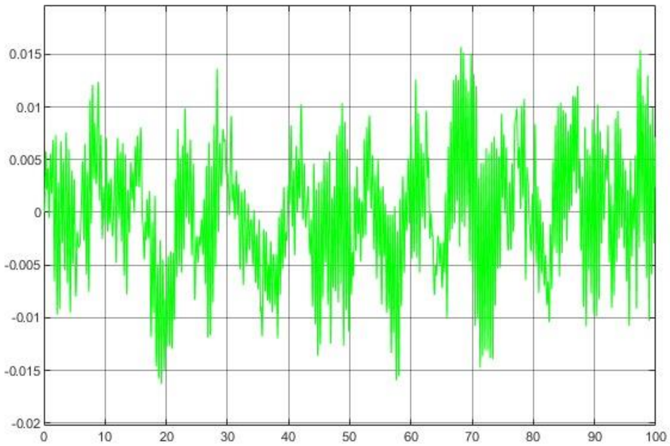

Figure – 14: Unsprung Mass Displacement for PID

Figure 14 represents the Displacement of Unsprung mass by a PID Controller. Graph shows us Displacement (m) on Y-axis and time (s) on X-axis. The changes of unsprung mass tell us about how much of the disturbances to the system will be transferred further on to the sprung mass.

3.2 RL Results

The results obtained for PID controller are shown below:

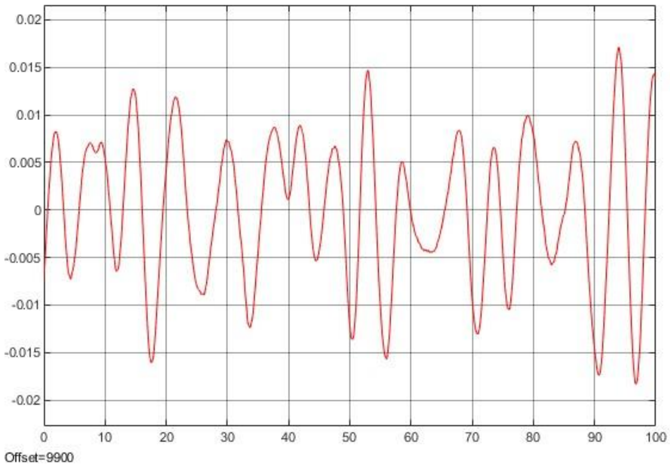

Figure – 15: Sprung Mass Displacement for RL Controller

Figure 15 represents the Sprung mass displacement for RL Controller. Here the maximum displacement was approximately 0.0155 m which is slightly higher than compared to the PID controller. This behaviour was expected as the RL Controller first needs to learn the system and then it optimizes it.

In Figure 16, Acceleration vs Time graph is shown for Sprung mass controlled by RL controller. The maximum acceleration values are seen slightly higher than the PID results. But the overall changes are far less than that.

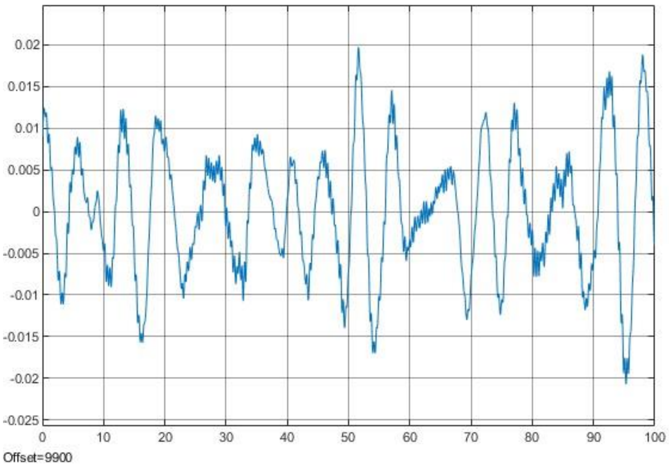

Figure – 16: Sprung Mass Acceleration for RL Controller

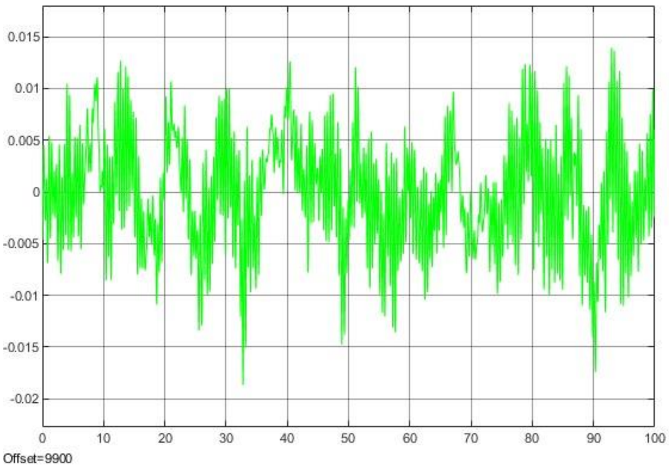

Figure – 17: Unsprung Mass Displacement for RL Controller

Similar to PID, Figure 17 represents the displacement of Unsprung mass with respect to time.

Comparing Sprung mass Displacement of PID with RL gave a **25.46 %** difference and Sprung mass Acceleration of PID with RL difference was of 15.97 %.

4. CONCLUSIONS

4.1 Conclusions:

1. The RL controller is better at handling larger non-linear equations as compared to PID controller.
2. Sprung mass displacement with RL controller was reduced by **25.46 %** with respect to PID controller.
3. Sprung mass acceleration with RL controller is also seen to be reduced by **15.97 %** as compared to PID controller.
4. PID controller requires fine tuning which is difficult to attain while RL controller just needs a correct Reward function to optimize the outputs.
5. Time taken by PID controller is much lesser than that of RL controller. A RL controller requires more computing power stating that it needs a reliable and faster system for the controller to operate efficiently.

4.2 Future Scope:

This paper is just limited to comparison of RL with PID controller. In this research only DDPG algorithm was tested against a PID tuner, but there are many more available Agents as mentioned above in the literature that needs to be tested and tried before concluding on the overall system.

ACKNOWLEDGEMENT

I express my sincere gratitude to **Dr. H. P. Khairnar**, Professor Mechanical Engineering Department VJTI – Mumbai for their expert guidance, invaluable suggestion and encouragement throughout the project work. His readiness to help at any hour coupled with his personal interest made it possible to complete this work.

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BIOGRAPHIES

Akash Anant Veer,
MTech Automobile Engineering,
Department of Mechanical Engineering,
VJTI, Mumbai, India