

A Traction Control System based on Co-evolutionary Learning in Spiking Neural Network (SNN)

Speaker:

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Authors:

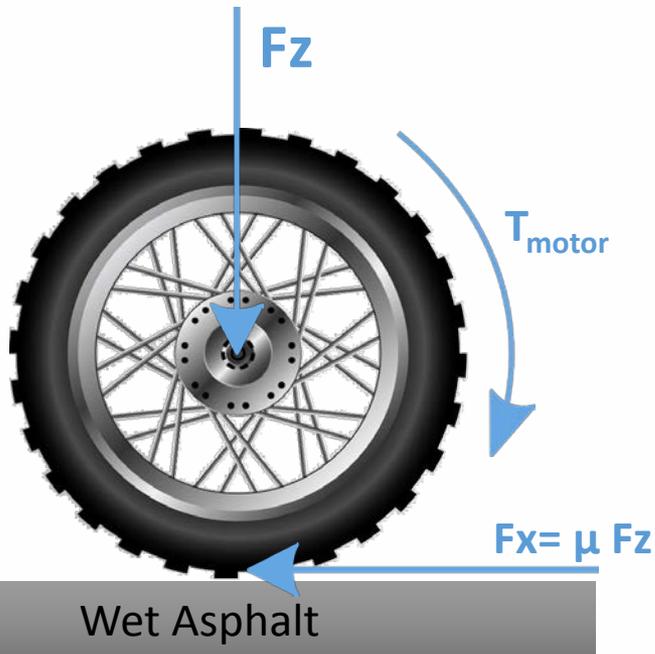
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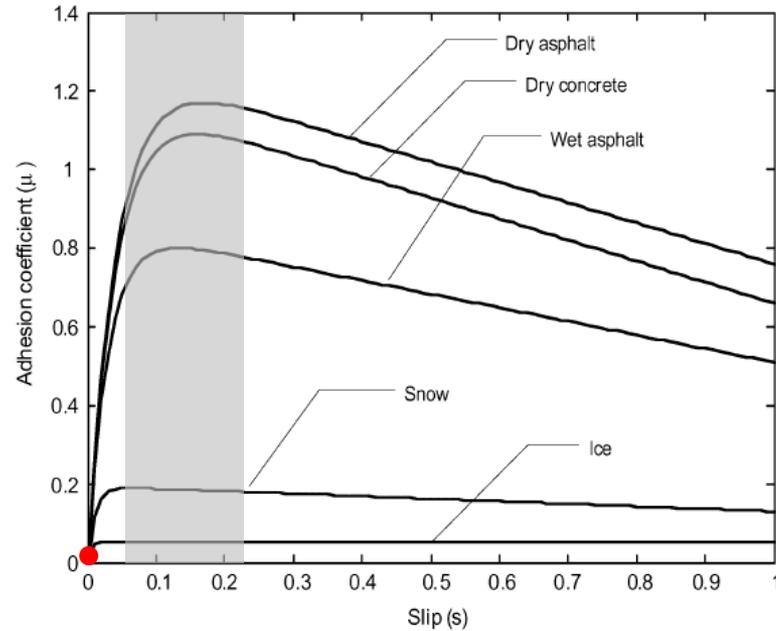
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- 1. Introduction**
2. Motorcycle Model
3. Control Spiking Neural Network
4. Co-evolution Learning
5. Results
6. Conclusion

TCS Operation



Adhesion characteristic curves



Wheel slip

$$s_r = 1 - \frac{V_x}{\omega_r R_r}$$

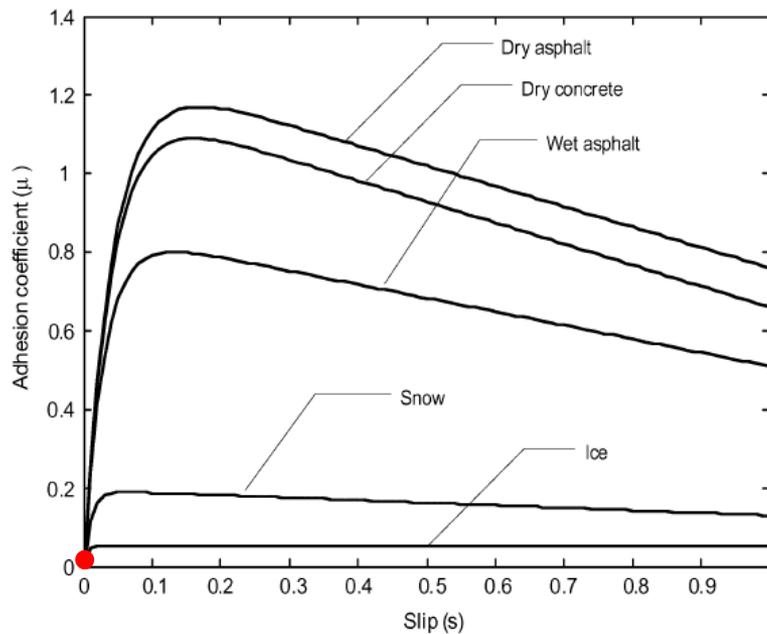
TCS Operation

(Road change high-low)



Dry Asphalt

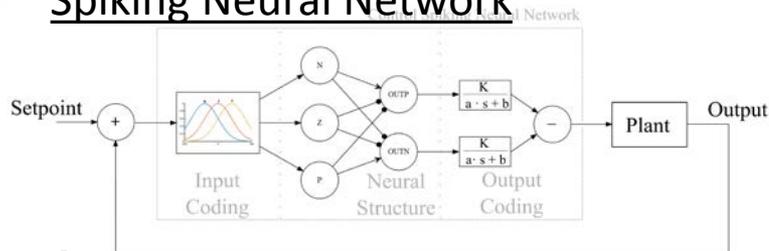
Adhesion characteristic curves



Wheel slip

$$s_r = 1 - \frac{V_x}{\omega_r R_r}$$

Spiking Neural Network



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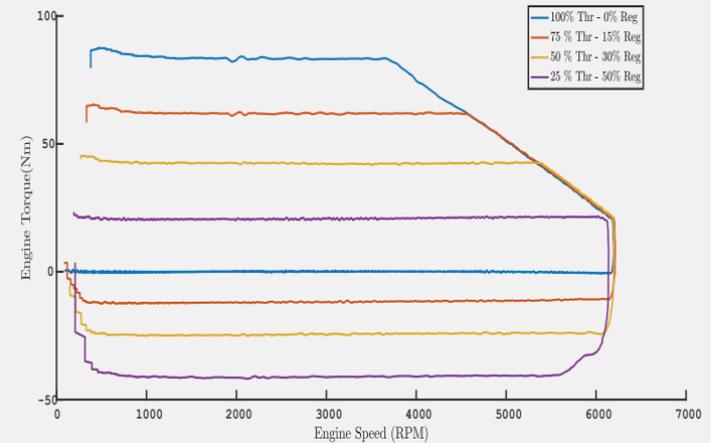
Motorcycle Model

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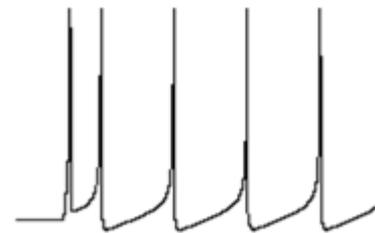
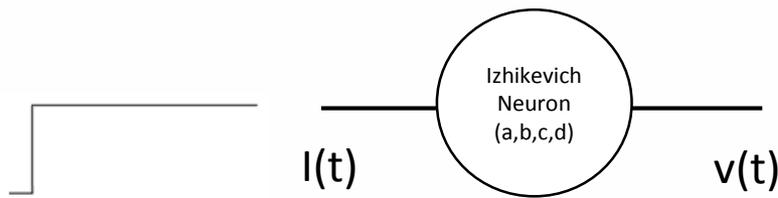
Component	Parameter	Description
Vehicle	Motorcycle weight	135 Kg
	Chassis Type	Steel Tubular
	Height of gravity centre	621 mm
	Distance between axis	1370 mm
	Wheel radius	300 mm
	Distance from the COG to the front axle	670 mm
	Front tire	95/70 R 17
	Rear tire	115/70 R 17
Electric motor	Brand	Heinzmann PMS 150
	Type	Axial Flux Permanent Magnet
	Maximum speed	6000 rpm
	Maximum torque	80 Nm
	Torque constant (K_m)	0.145 Nm/A
Maximum power	34.1 KW (46.36 CV)	
Battery	Battery Type	LiPo
	Cell layout	26S5P
	Total capacity	4.8 KWh
	Rated Voltage	96 V
	Maximum discharge current	1250 A
Maximum load current	300 A	

Motor Model



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Izhikevich Neuron Model

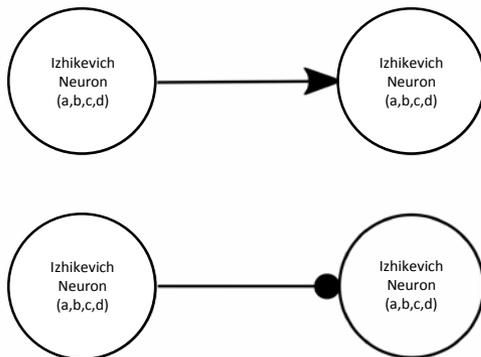


$$\frac{dv}{dt} = 0.94v^2 + 5v + 140 - u + I(t)$$

$$\frac{du}{dt} = a(bv - u)$$

$$\text{If } v \geq 30 \text{ then } \begin{cases} v \leftarrow c \\ u \leftarrow u + d \end{cases}$$

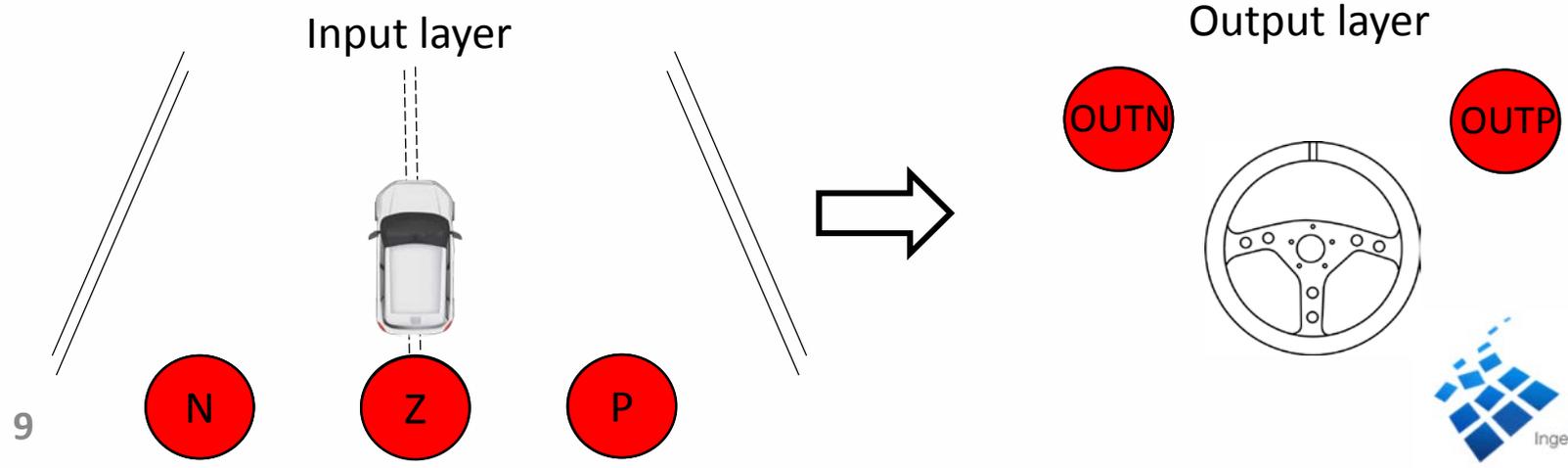
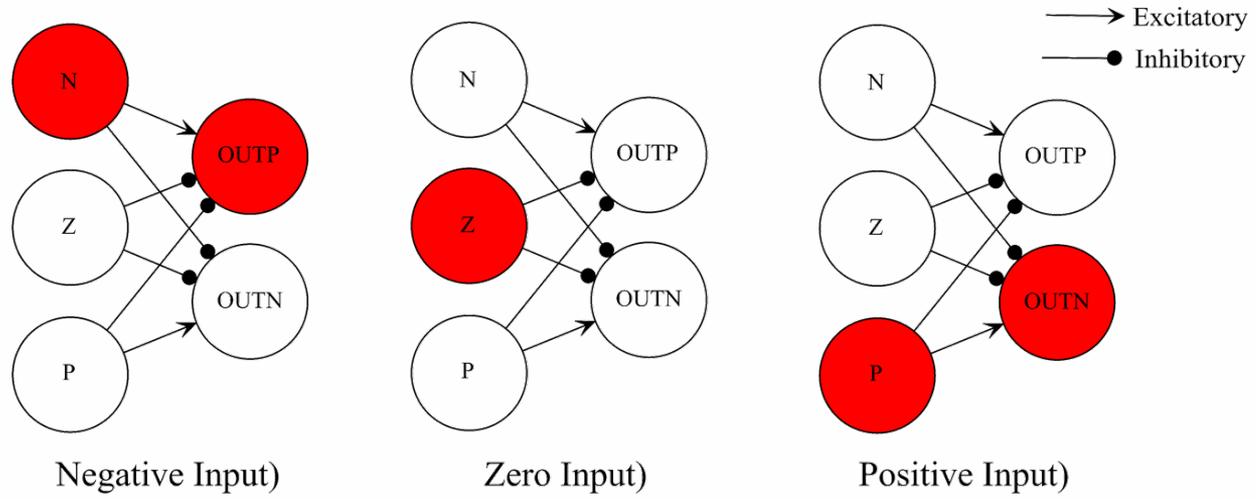
Synapse Model



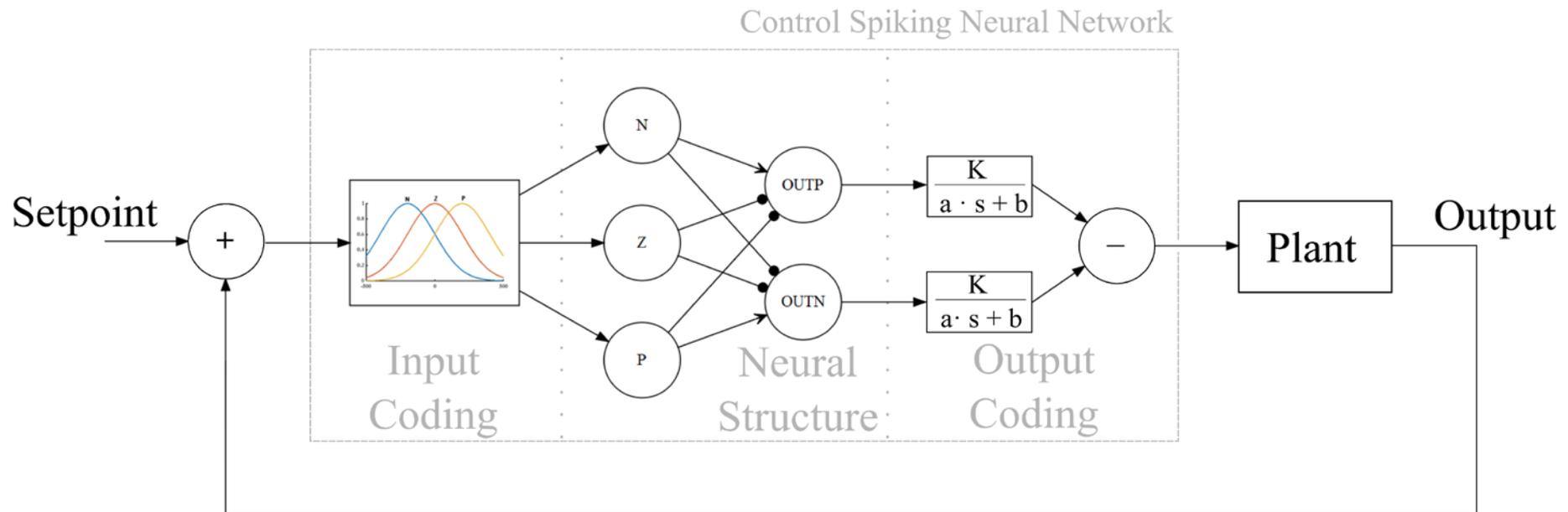
$$I(t) = w_{ij} \varepsilon(t - t_{spike})$$

$$\varepsilon(t - t_{spike}) = \begin{cases} \frac{t - t_{spike}}{\tau} e^{-\frac{t - t_{spike}}{\tau}}, & \text{if } t \geq t_{spike} \\ 0, & \text{if } t < t_{spike} \end{cases}$$

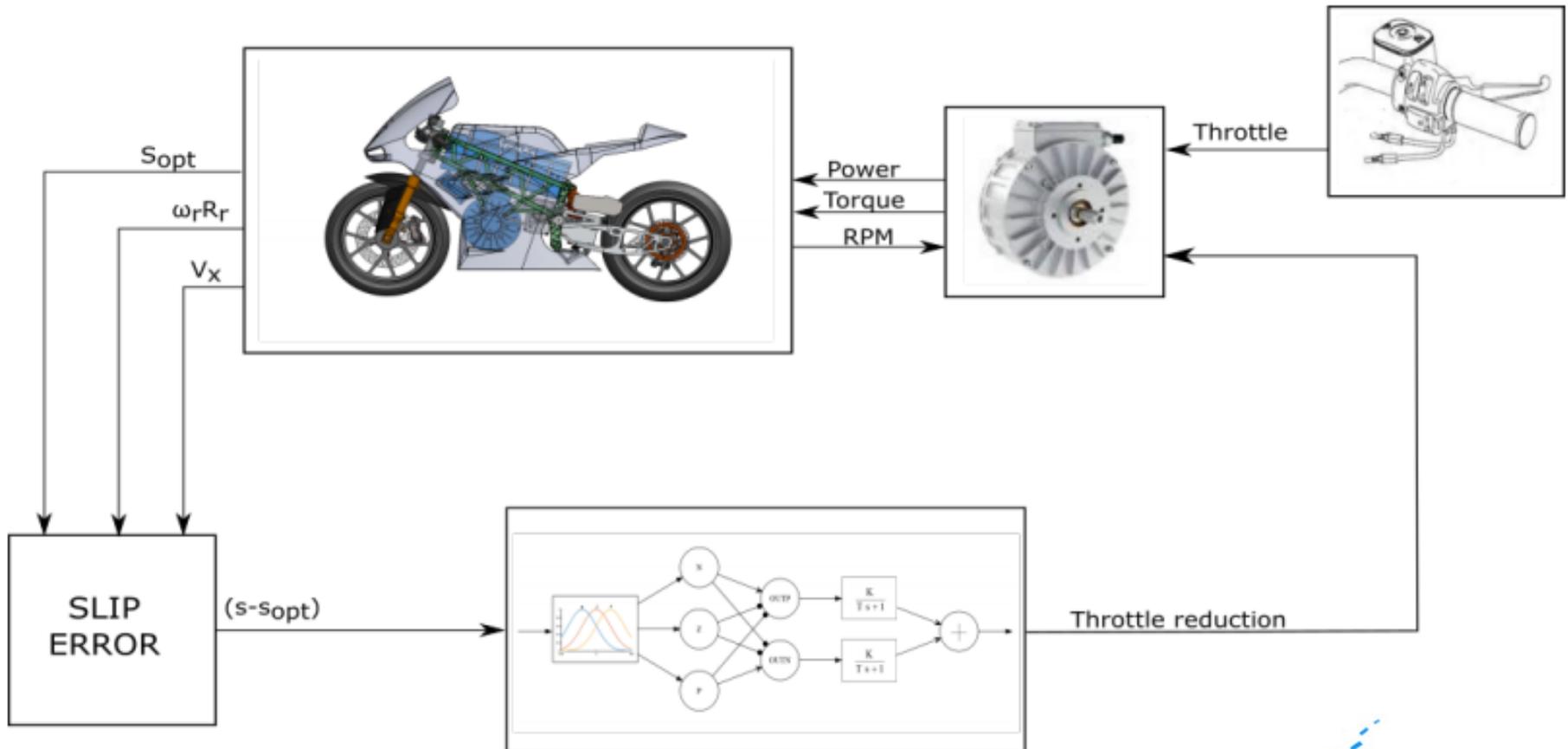
Neural Network Operation



Neural Network Structure



Neural Network Scheme

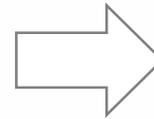
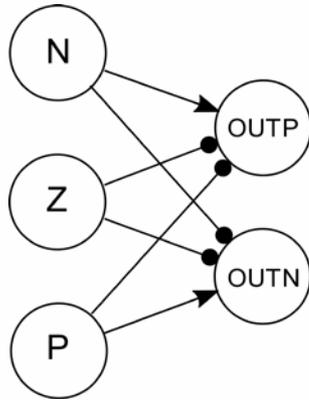


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Co-evolution Learning

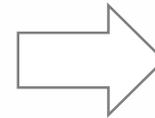
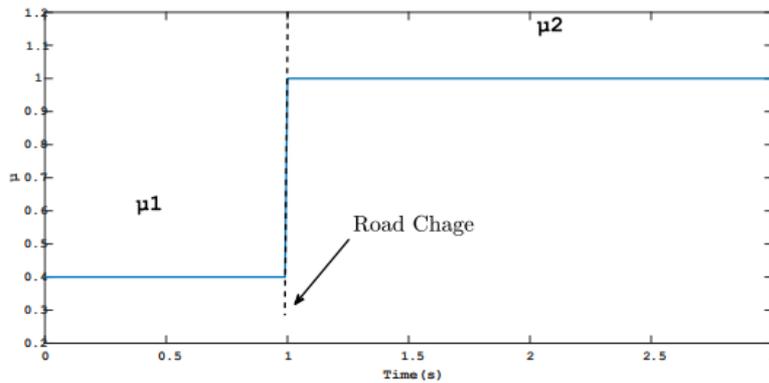
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Prey



W_{1_1}	W_{2_1}	W_{3_1}	W_{4_1}	W_{5_1}	W_{6_1}
W_{1_2}	W_{2_2}	W_{3_2}	W_{4_2}	W_{5_2}	W_{6_2}
W_{1_3}	W_{2_3}	W_{3_3}	W_{4_3}	W_{5_3}	W_{6_3}
			:		
			:		
			:		
			:		
W_{1_n}	W_{2_n}	W_{3_n}	W_{4_n}	W_{5_n}	W_{6_n}

Predator

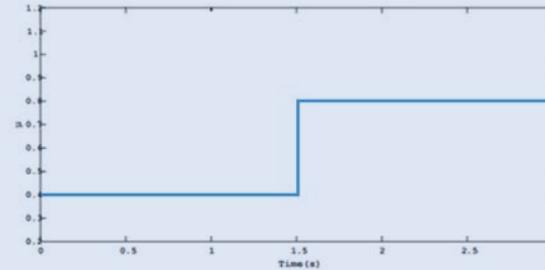
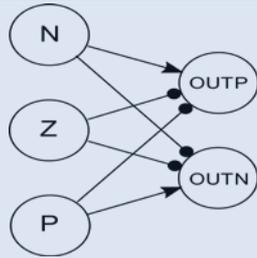


μ_{1_1}	t_{1_1}	μ_{2_1}
μ_{1_2}	t_{1_2}	μ_{2_2}
μ_{1_3}	t_{1_3}	μ_{2_3}
		:
		:
		:
μ_{1_n}	t_{1_n}	μ_{2_n}

Training Method (Genetic Algorithm)

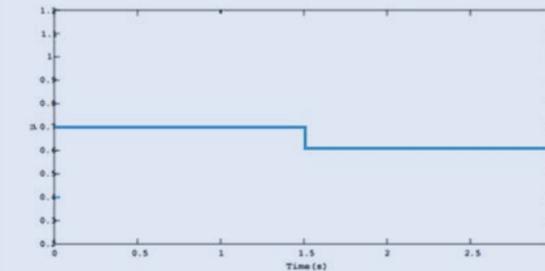
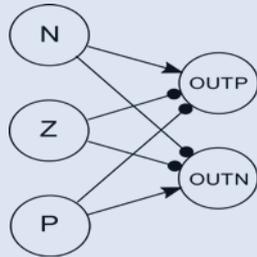
Training #0

Control #0



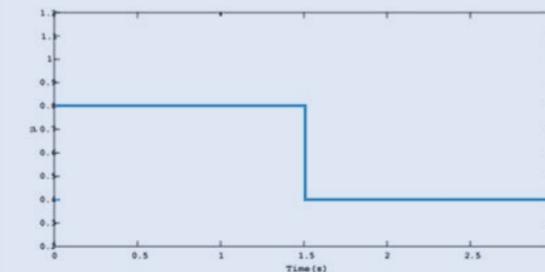
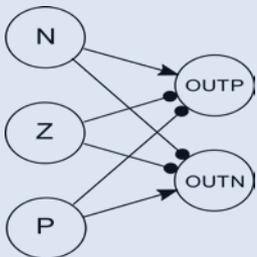
Test #0

Control #1



Test #1

Control #2



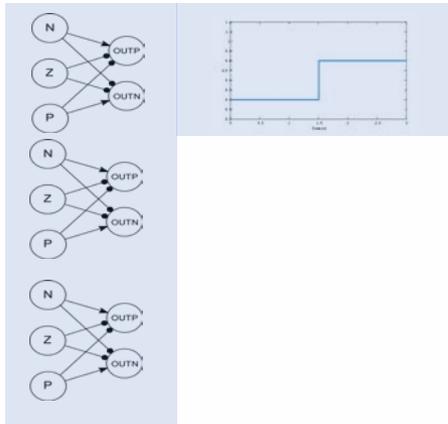
Test #2

Co-evolution Learning

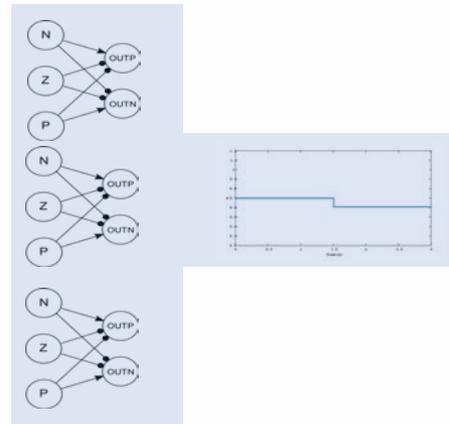
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(Genetic Algorithm)

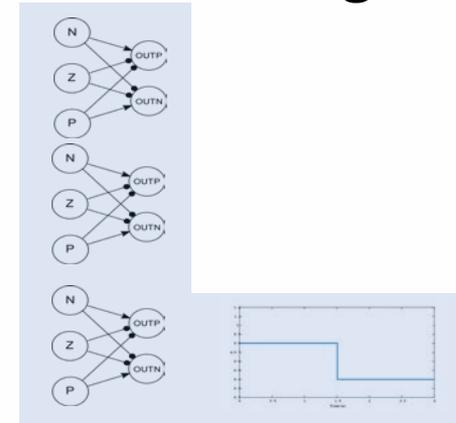
Training #0



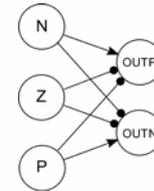
Training #1



Training #2



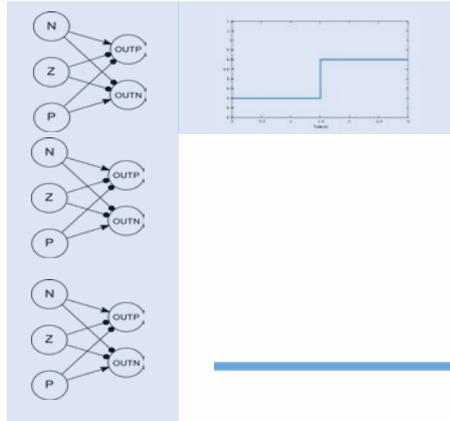
Best Controller



Co-evolution Learning

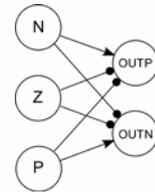
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Training #0

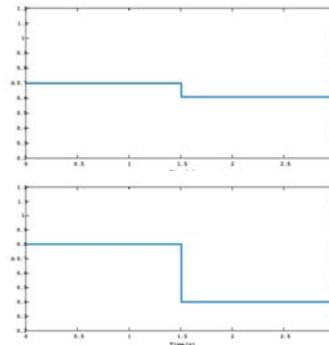
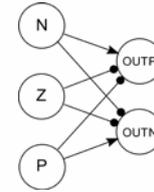


(Co-evolutionary Algorithm)

Best Controller



Best Controller



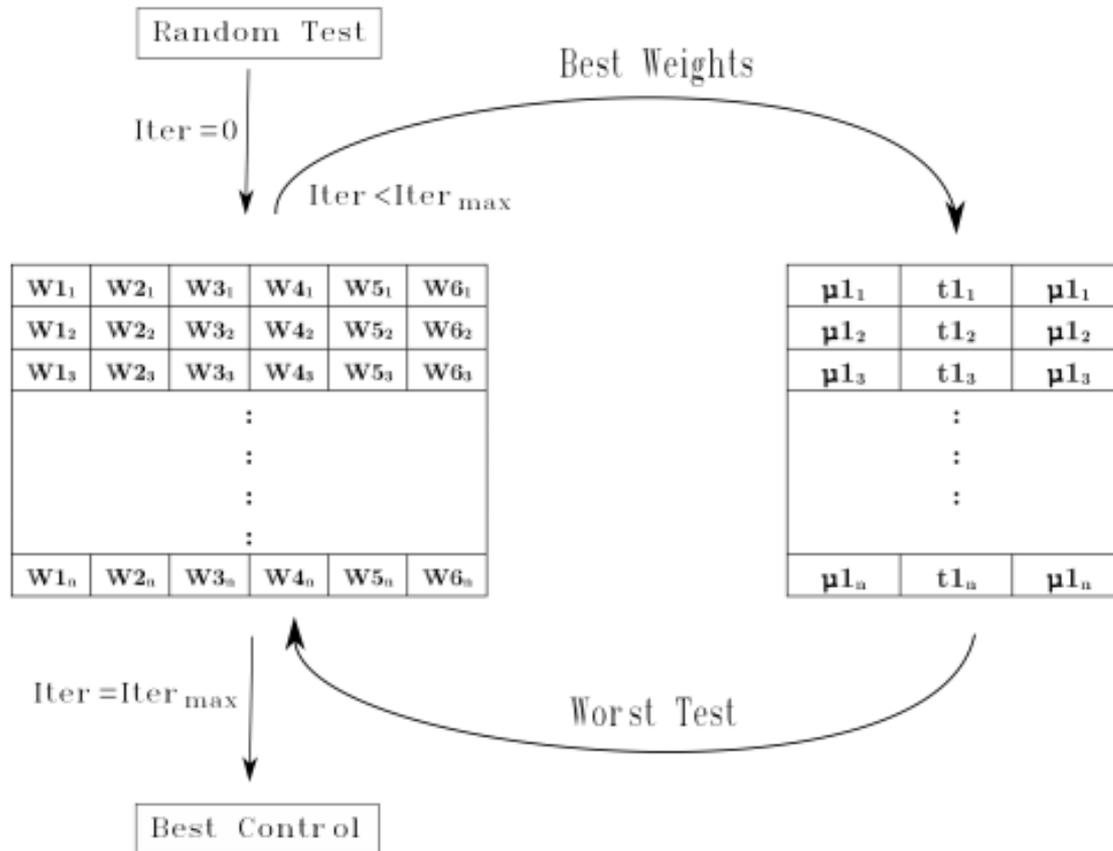
Worst Test

Training #1



Co-evolution Learning

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$$e(\mu_1, t_1, \mu_2) = \left(\frac{m_1}{mt_1} + \frac{m_2}{mt_2} \right)^2$$

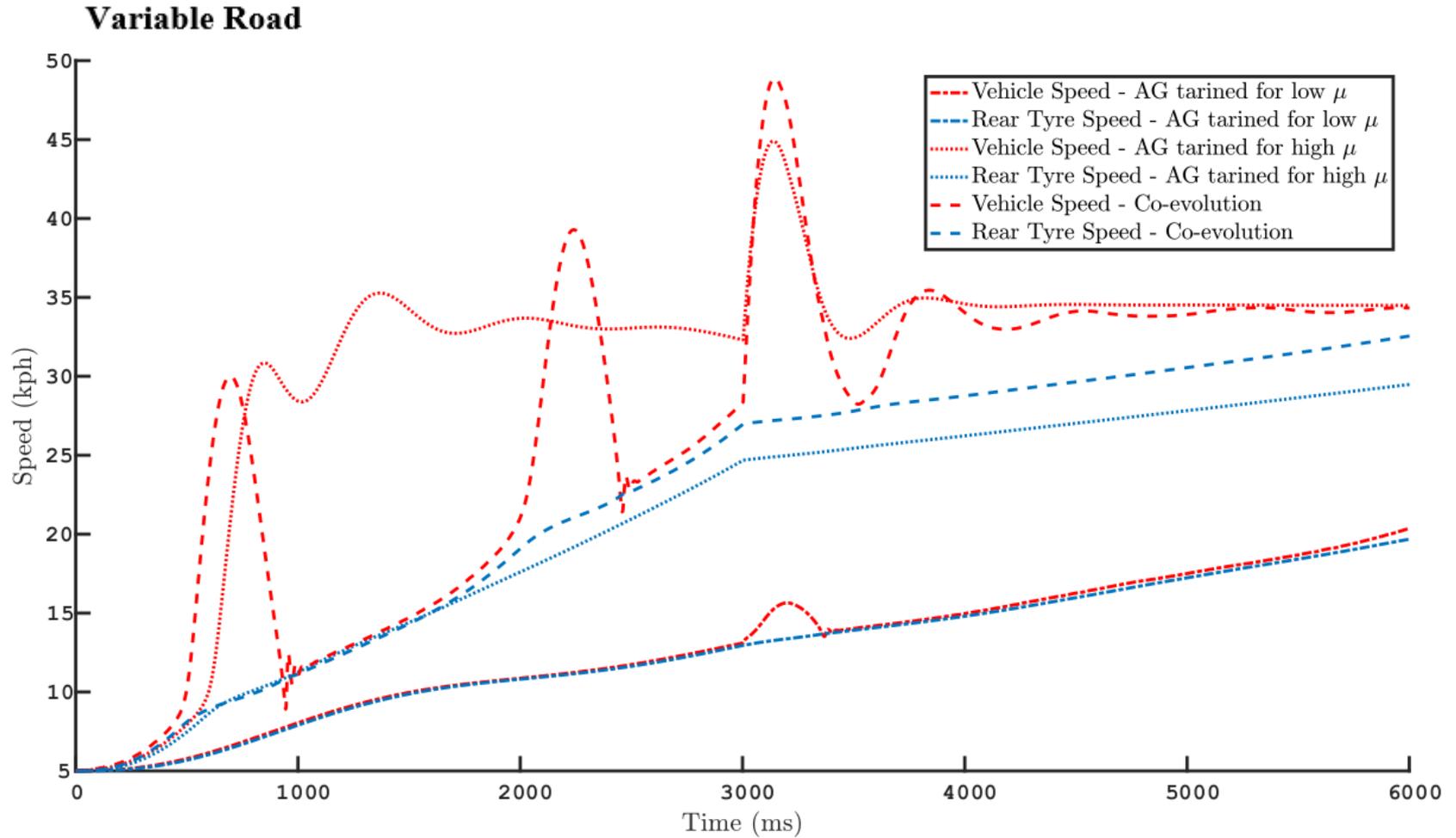
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Table 1 Error value for constant road test

Road	$\mu = 0.2$	$\mu = 0.4$	$\mu = 0.6$	$\mu = 0.8$	$\mu = 1$	Σe
AG Train $\mu = 0.2$	1.0000	0.8379	0.8267	0.7171	0.6237	4.0055
AG Train $\mu = 0.4$	0.9793	1.0000	0.8719	0.8685	0.7360	4.4556
AG Train $\mu = 0.6$	0.9183	0.8268	1.0000	0.7875	0.6276	4.1601
AG Train $\mu = 0.8$	0.9666	0.8619	0.9220	1.0000	0.8407	4.5911
AG Train $\mu = 1$	0.9017	0.7667	0.9090	0.8884	1.0000	4.4658
Co-evolutionary	0.9540	0.8851	0.9428	0.8639	0.9705	4.6162
Fuzzy Logic	0.9260	0.8314	0.9203	0.7885	0.6417	4.1079

Table 2 Error value for variable road test ($t_1=1.5s$)

Road	$\mu = 0.2$ $\mu = 0.6$	$\mu = 0.6$ $\mu = 0.2$	$\mu = 1$ $\mu = 0.4$	$\mu = 0.4$ $\mu = 1$	$\mu = 0.6$ $\mu = 0.4$	$\mu = 0.4$ $\mu = 0.6$	Σe
AG Train $\mu = 0.2$	0.8177	0.7705	0.6337	0.9391	0.8092	0.8966	4.8668
AG Train $\mu = 0.4$	1.0000	0.8776	0.7468	0.8847	0.8808	1.0000	5.3898
AG Train $\mu = 0.6$	0.9250	1.0000	0.6721	0.9677	1.0000	0.9504	5.5152
AG Train $\mu = 0.8$	0.8591	0.9112	0.8415	0.8480	0.9053	0.9328	5.2979
AG Train $\mu = 1$	0.8533	0.8449	1.0000	1.0000	0.8554	0.8628	5.4164
Co-evolutionary	0.9292	0.9359	0.9689	0.9084	0.9481	0.9444	5.6349
Fuzzy Logic	0.9440	0.9965	0.6840	0.7431	0.9727	0.8737	5.2141



a) b)
Fig. 8.1 Variable road test from high to low adhesion ($\mu_1=0.8 \rightarrow \mu_2=0.4$)

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- A controller for motorcycle T.C.S. is presented. The method is based on the use of Spiking Neural Networks and is optimized to road variations.
- Simulations with BikeSim© confirm the performance of the proposed T.C.S in constant and variable roads
- The proposed controller has the best overall performance not only in constant adherence conditions but also when adherence changes during the test.



In future works, tests will be carried out on real roads with an electric bike.

Conclusion

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NO Control



Fuzzy Control



A Traction Control System based on Co-evolutionary Learning in Spiking Neural Network (SNN)

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