Deep Neural Network based Power Management System Control for Hybrid Vehicle

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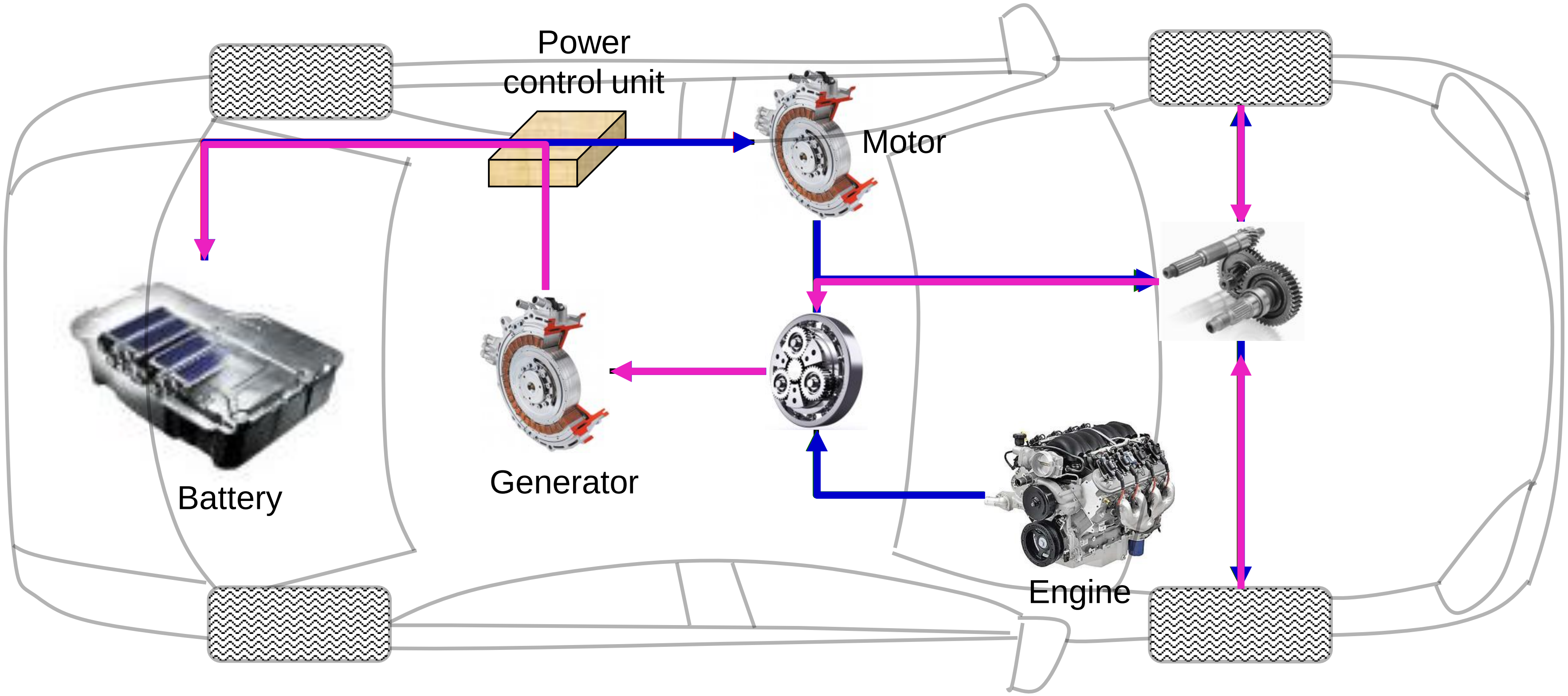
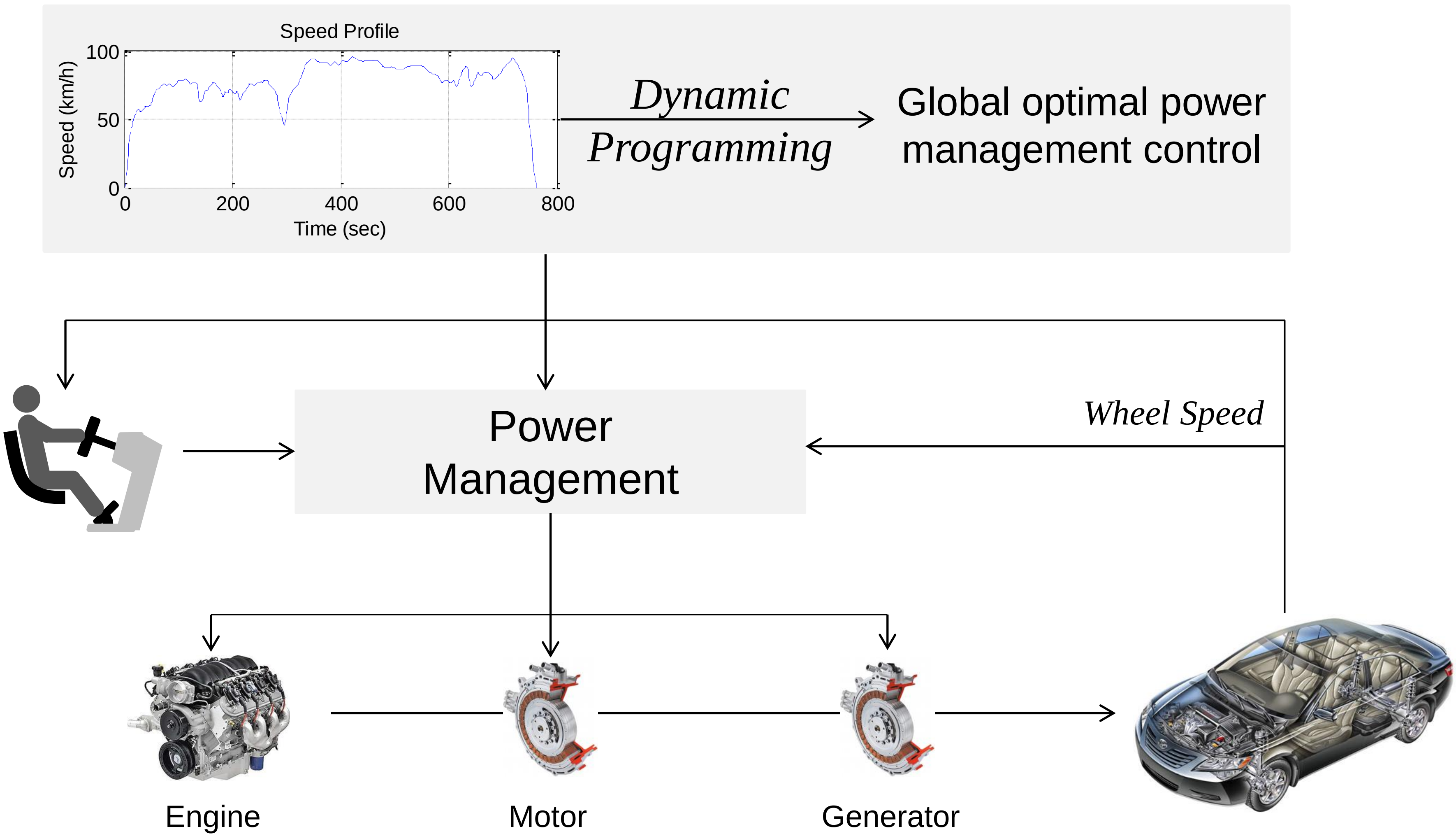
Introduction

Power Management System for HEV



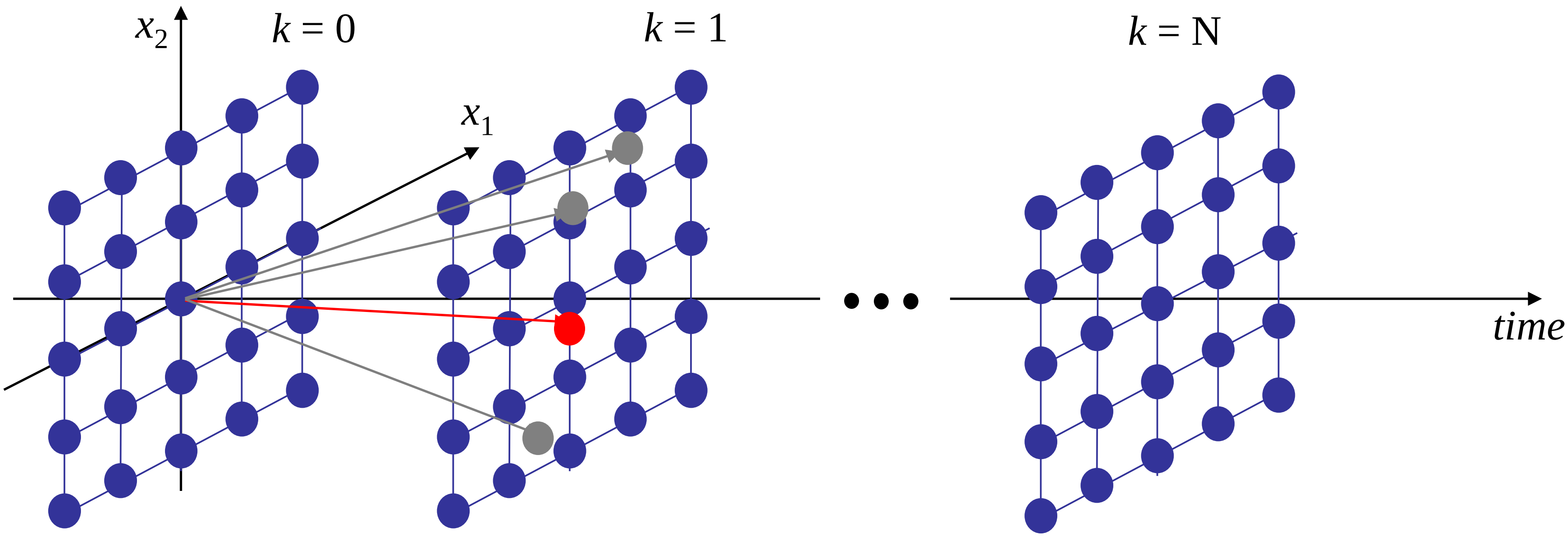
Optimal PMS Control

- Dynamic Programming based PMS control strategy



Dynamic Programming

- Global optimal method, but not practical



$$J_k^*(x_k) = \min_{u_{1,k}, u_{2,k}} [L(x_k, u_k)]$$

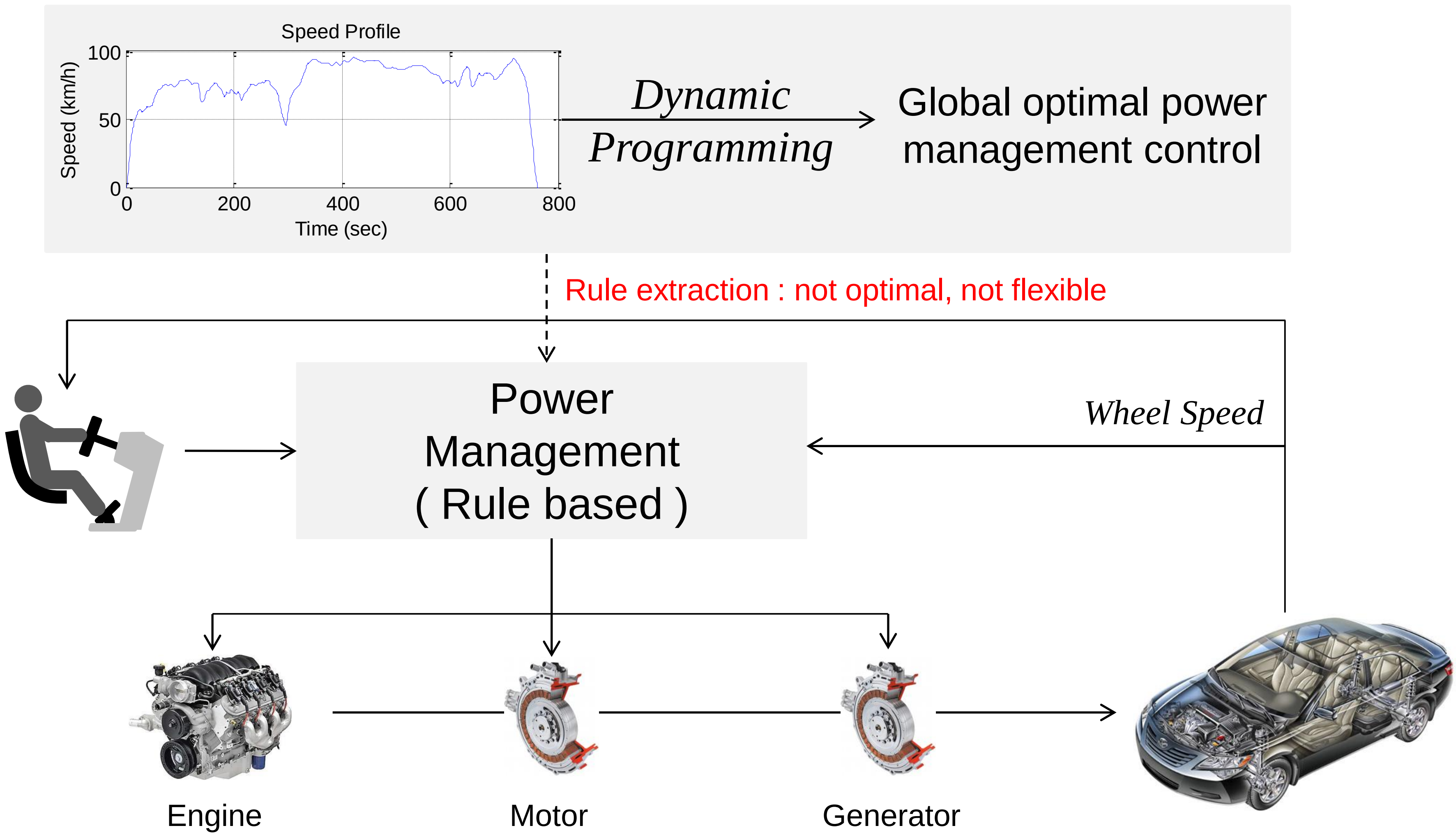
$$J_N^*$$

$$\text{minimize } J = \sum_{k=0}^{N-1} [J_k^*(x_k)] + J_N^*$$

Requires future information ➔ Impractical method in real

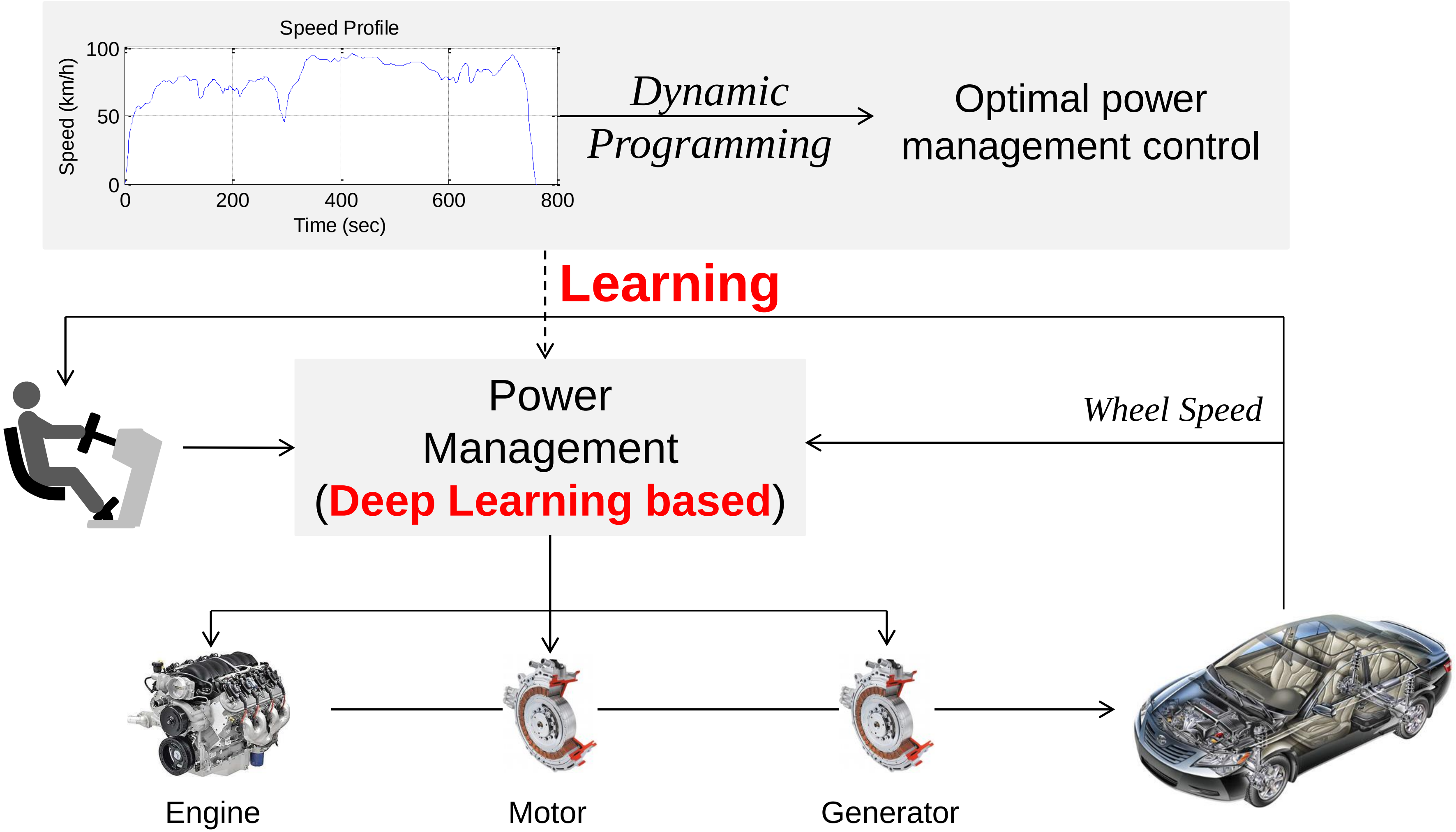
Practical PMS Control

- Rule based PMS control strategy in real environment



Proposed Research

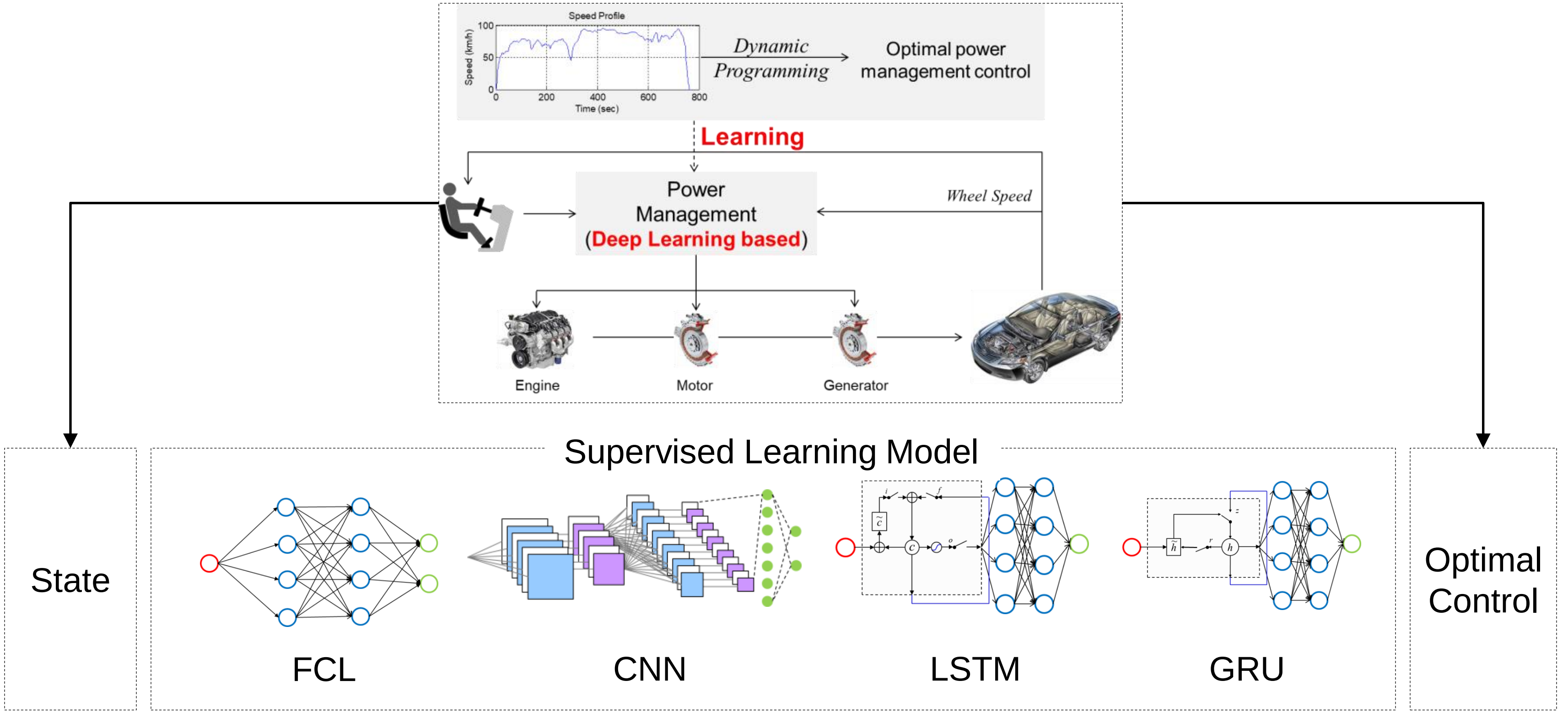
- Development of deep learning based PMS control strategy



Objective

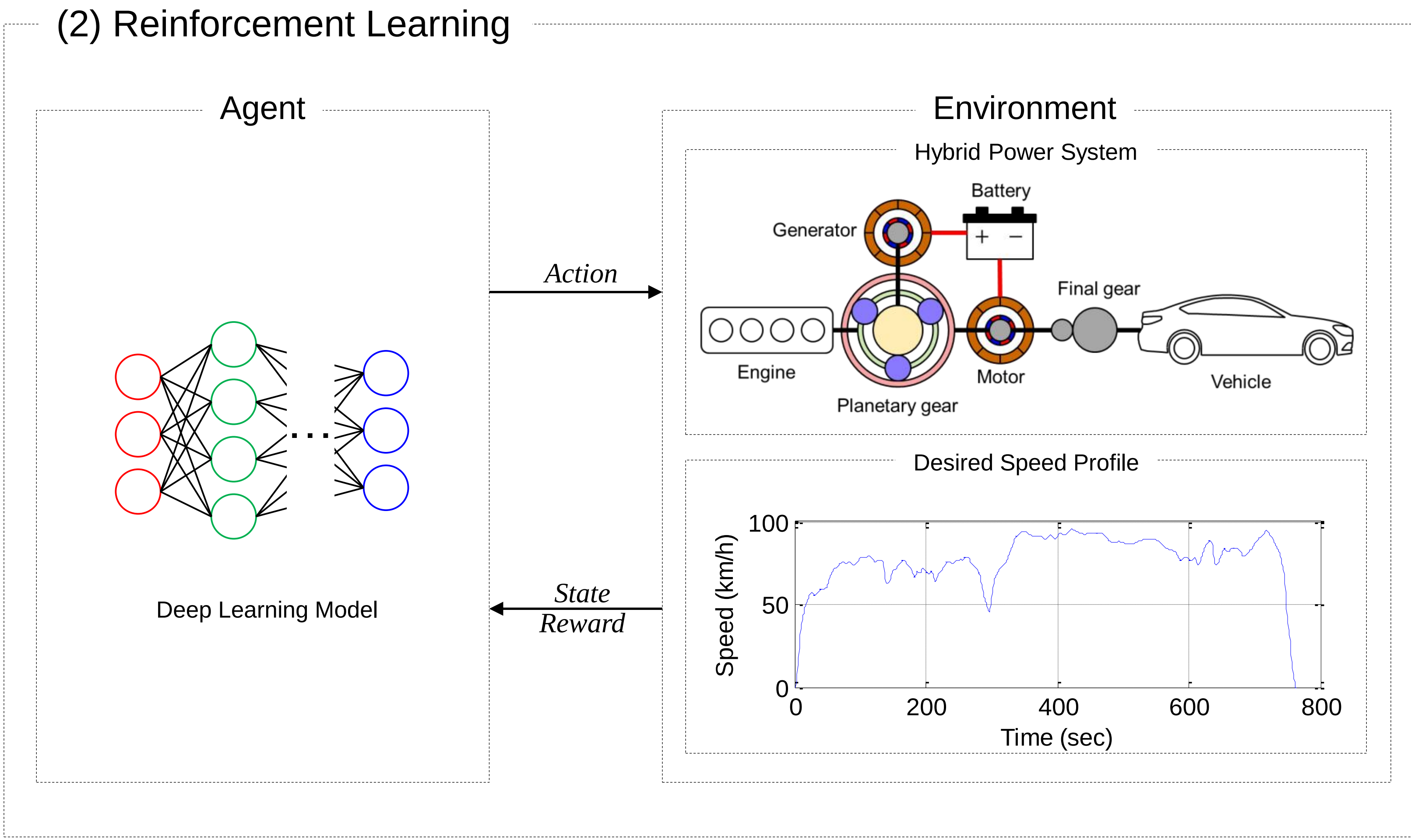
- Deep learning based model design for getting higher fuel efficiency

(1) Supervised Learning



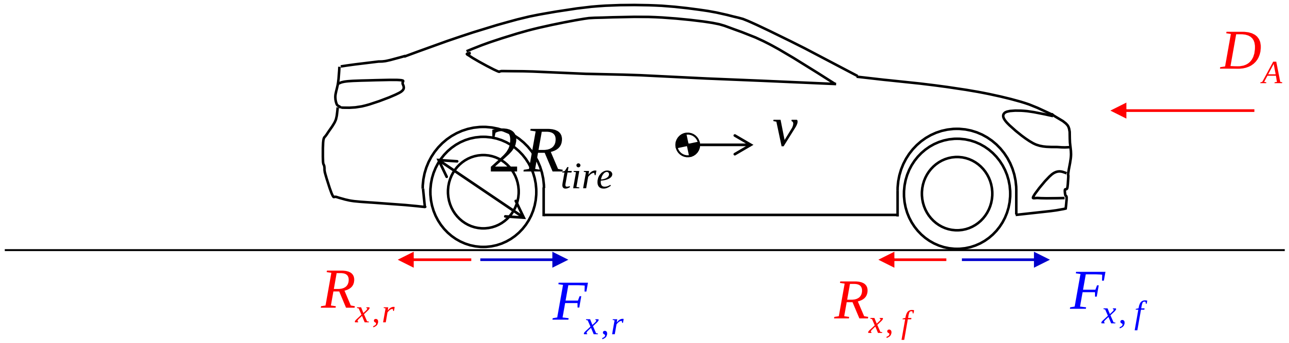
Objective

- Deep learning based model design for getting higher fuel efficiency



Vehicle Model

Longitudinal Vehicle Model



Aerodynamic drag force $= \frac{1}{2}\rho_{air} A_f C_d v^2$

$$M\dot{v} = (F_{x,f} + F_{x,r}) - D_A - (R_{x,f} + R_{x,r})$$

Traction force

Rolling resistance force $= f_v W = f_v Mg$

$$P_{v[k]} = \left(F_{x,f} + F_{x,r}\right) v_{[k]}$$

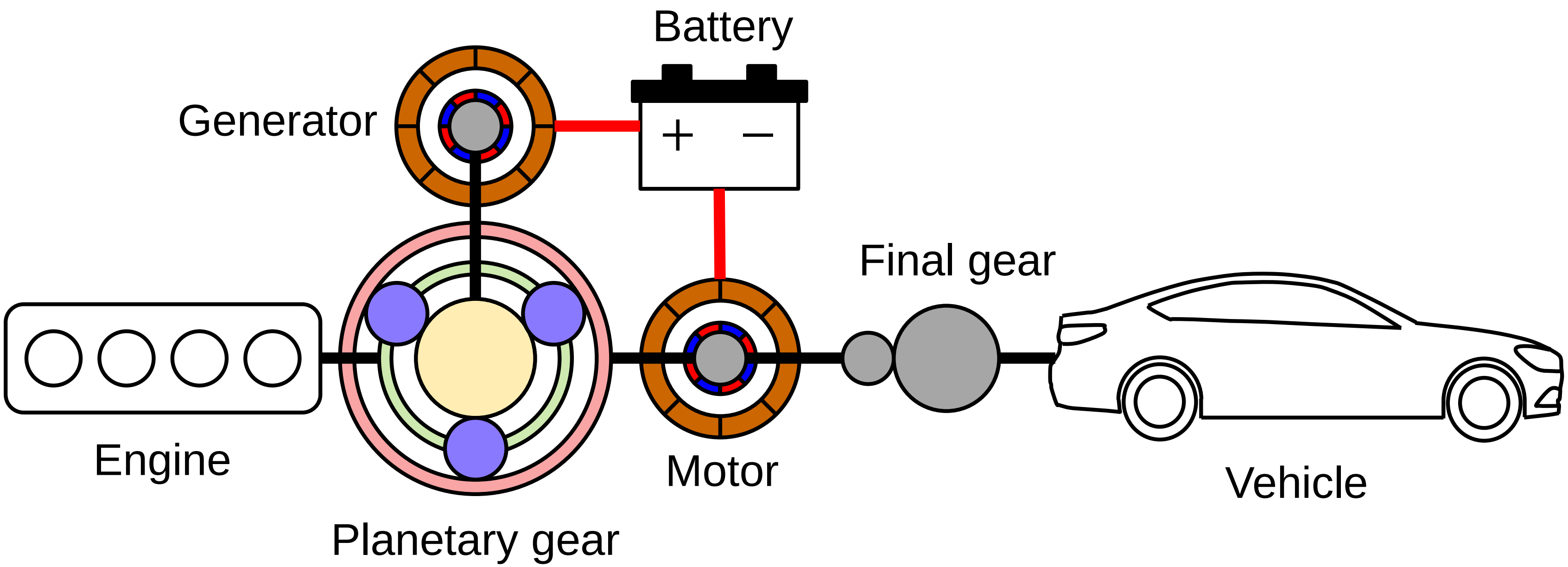
$\rho_{air} = air\ density[kg/m^3]$

$A_f = vehicle\ frontal\ area[m^2]$

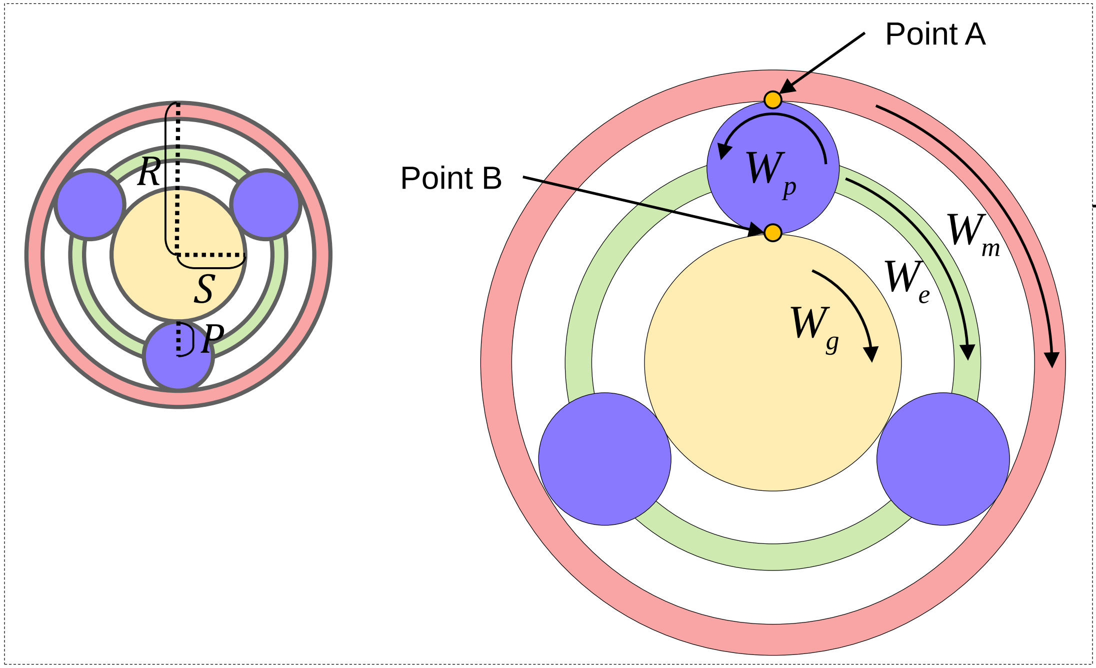
$C_d = aerodynamics\ drag\ coefficient$

$f = rolling\ resistance\ coefficient$

Hybrid Power System



Kinematics of Hybrid Power System



At point A

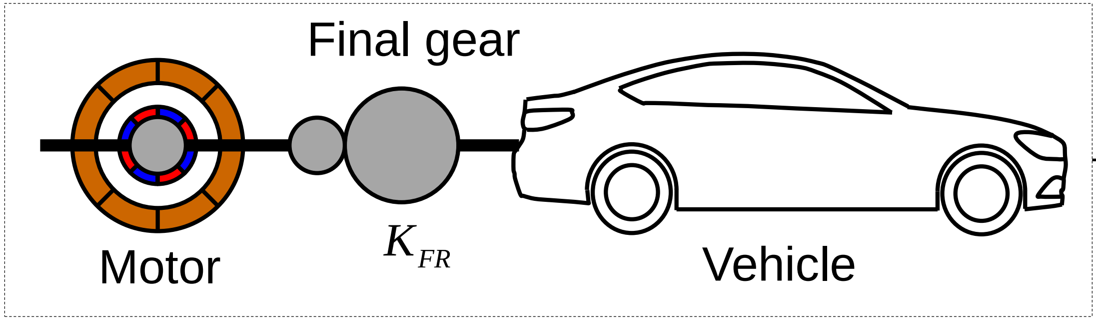
$$W_m R = W_e(2P+S) - W_p P$$

At point B

$$W_g S = W_e S + W_p P$$

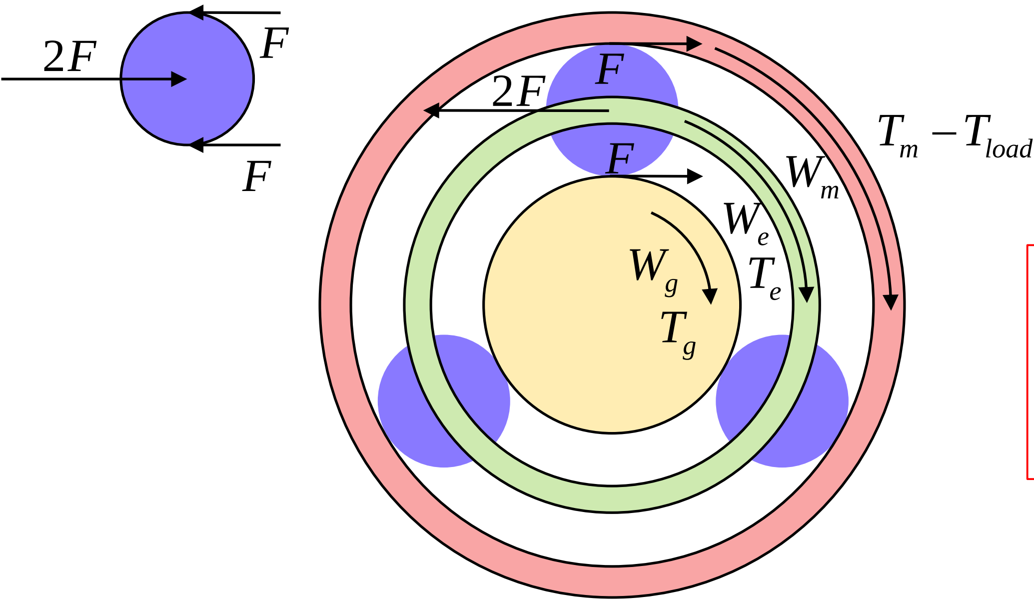
$$R = 2P + S$$

$$\boxed{W_g S + W_m R = W_e (R+S)}$$



$$\boxed{W_v = K_{FR} W_m}$$

Dynamics of Hybrid Power System



$$
\boxed{
\begin{aligned}
&T_g + SF = I_g \dot{W}_g \\
&T_m - T_{load} + RF = I_m \dot{W}_m \\
&T_e - (R+S)F = I_e \dot{W}_e
\end{aligned}
}
$$

$$T_e - (S+P)\cdot 2F = I_e \dot{W}_e$$

$$R = 2P + S$$

Inertia of planetary gear is ignored

Dynamics Equation of Hybrid Power System

$$
\begin{bmatrix}
\left(\frac{R_{tire}}{K_{FR}}\right)^2 M + I_m & 0 & 0 & -R \\
0 & I_e & 0 & R+S \\
0 & 0 & I_g & -S \\
-R & R+S & -S & 0
\end{bmatrix}
\begin{bmatrix}
\dot{W}_m \\ \dot{W}_e \\ \dot{W}_g \\ F
\end{bmatrix}
=
\begin{bmatrix}
T_m - T_{load} \\ T_e \\ T_g \\ 0
\end{bmatrix}
$$

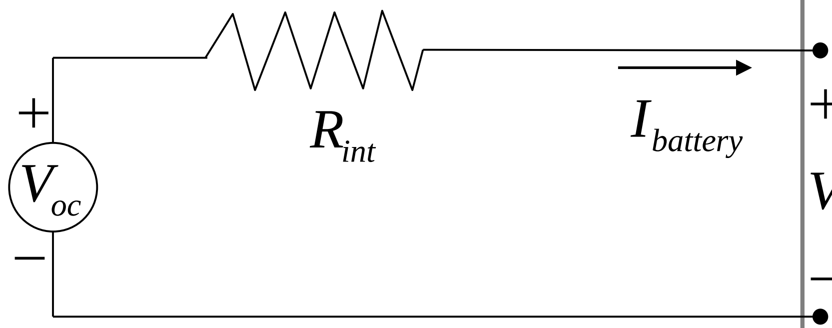
$$T_{load} = \left(M\dot{v} + Mgf_v + \frac{1}{2}\rho_{air} A_f C_d v^2 \right) R_{tire}$$

v: Velocity of the vehicle

Battery Dynamics

$$P_{battery} = V_{oc} I_{battery} - I_{battery}^{2} R_{int}$$

Resistance model



Battery power

$$P_{battery} = T_m W_m \eta_m{}^{k} + T_g W_g \eta_g{}^{k}$$

$$k = \begin{cases} -1, & discharge \\ 1, & charge \end{cases}$$

η_m : *efficiency of motor*

η_g : *efficiency of generator*

$$V_{oc} = f(\mathrm{SOC})$$

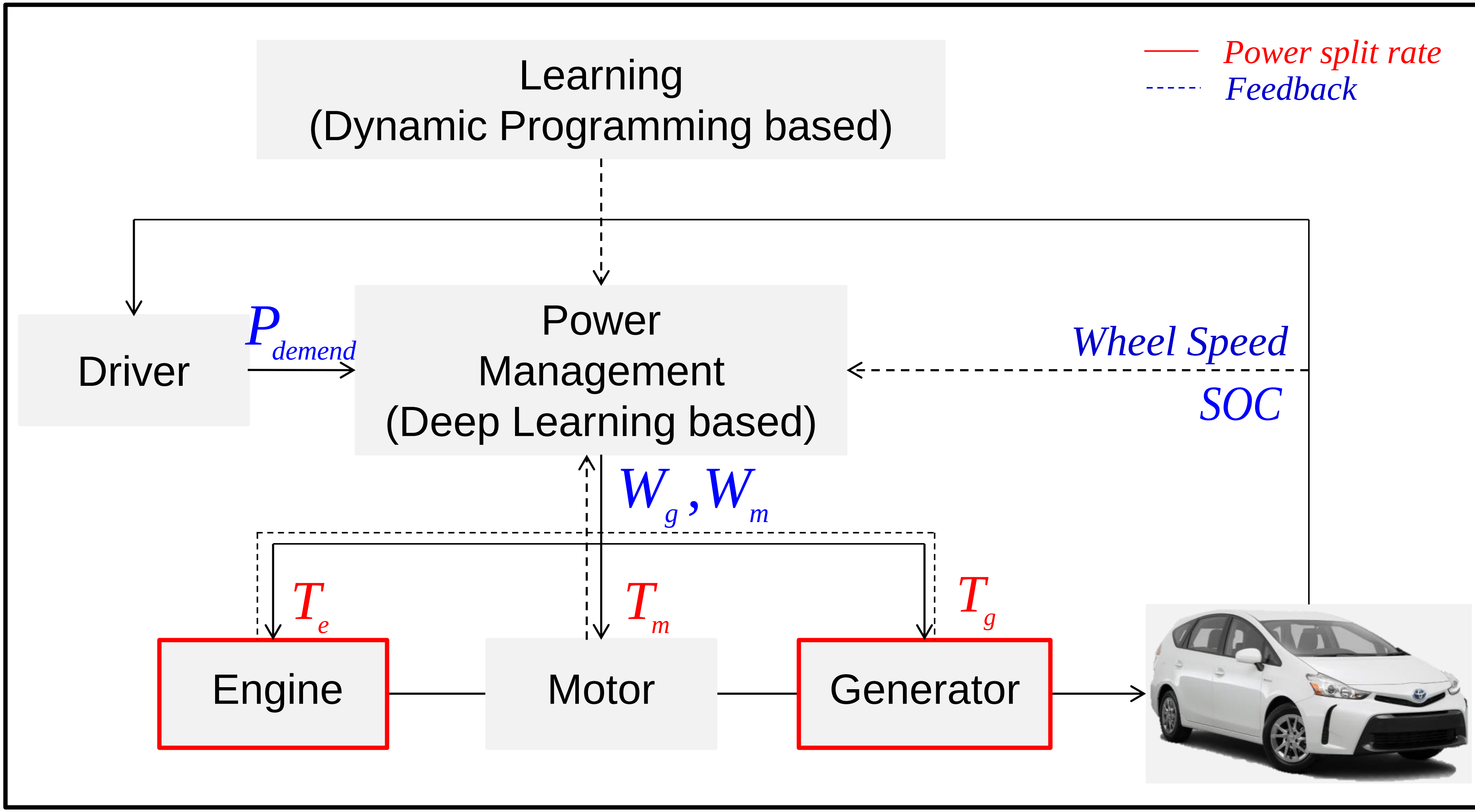
$$R_{int} = f(\mathrm{SOC}, charge / discharge)$$

$$\dot{SOC} = -\frac{I_{battery}}{C_{battery}}$$

$$\dot{SOC} = -\frac{V_{oc} - \sqrt{V_{oc}^{2} - 4(T_m W_m \eta_m{}^{k} + T_g W_g \eta_g{}^{k}) R_{int}}}{C_{battery}}$$

$C_{battery}$: *battery capacity*

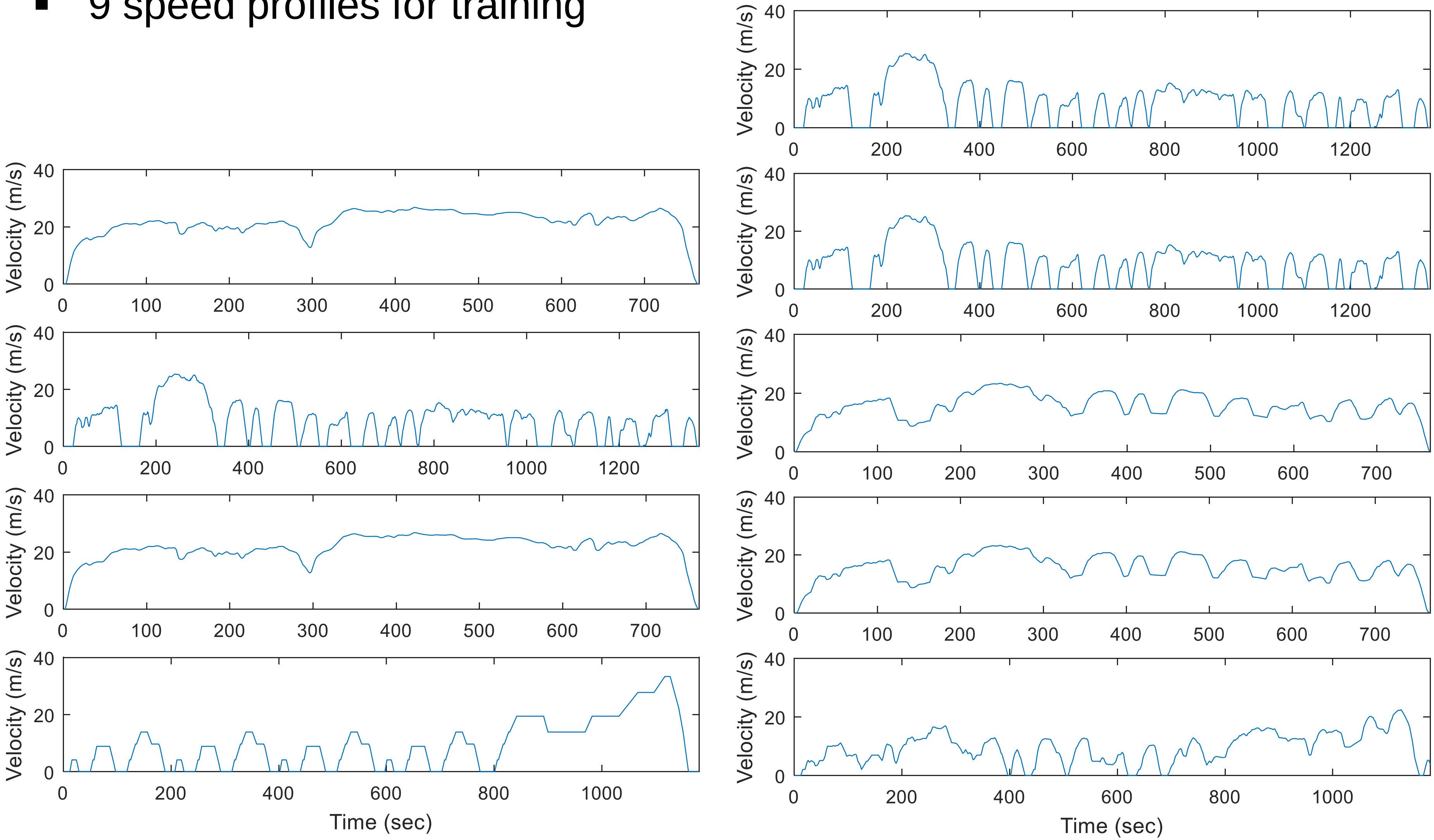
Apply to Vehicle



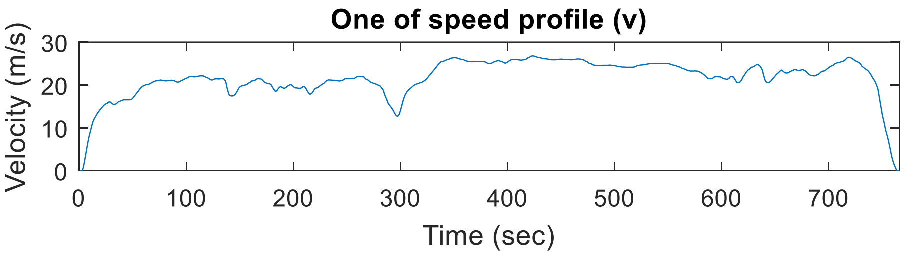
Training Data

Speed Profiles

- 9 speed profiles for training



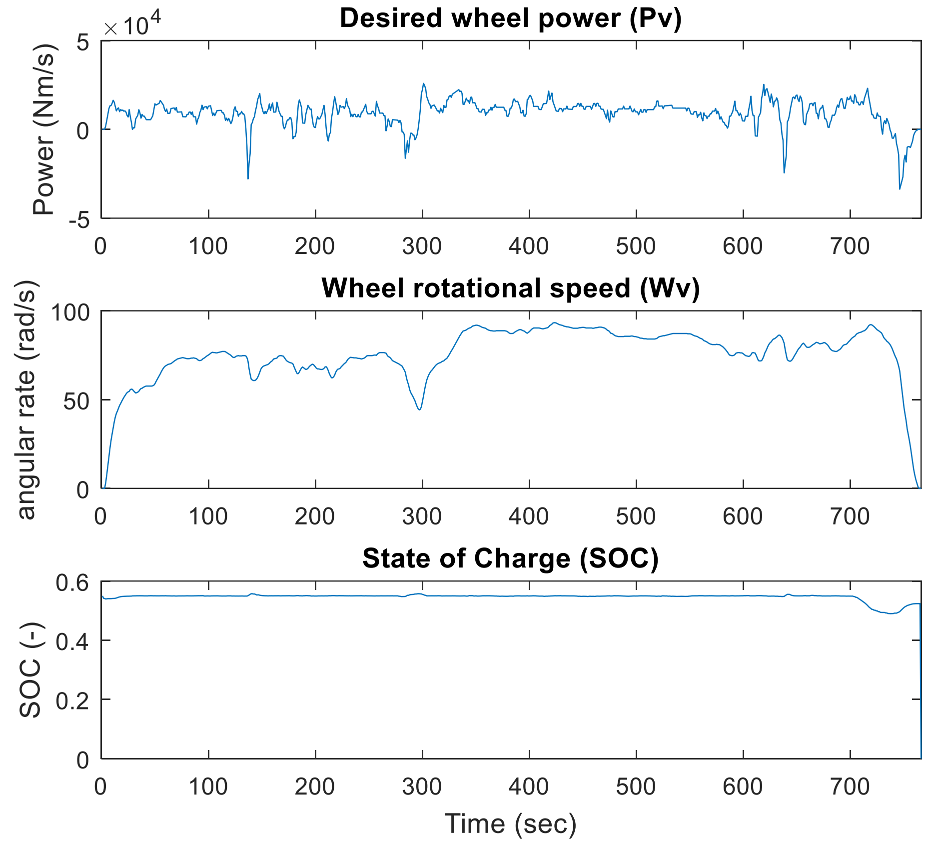
Additional Features from Speed Profiles



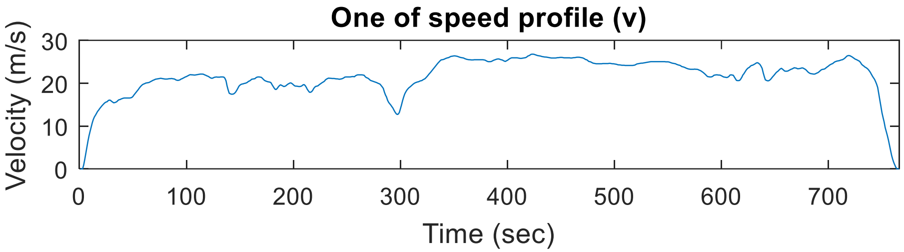
$$P_{v[k]} = \left(M\dot{v}_k + Mgf_v + \frac{1}{2}\rho_{air} A_f C_d {v_{[k]}}^2 \right) v_{[k]}$$

$$W_{v[k]} = \frac{v_{[k]}}{R_{tire}}$$

$$SOC_{[k]} = SOC_{[k-1]} + dSOC_{[k-1]} \cdot dt,\ SOC_{[0]} = 0.55$$



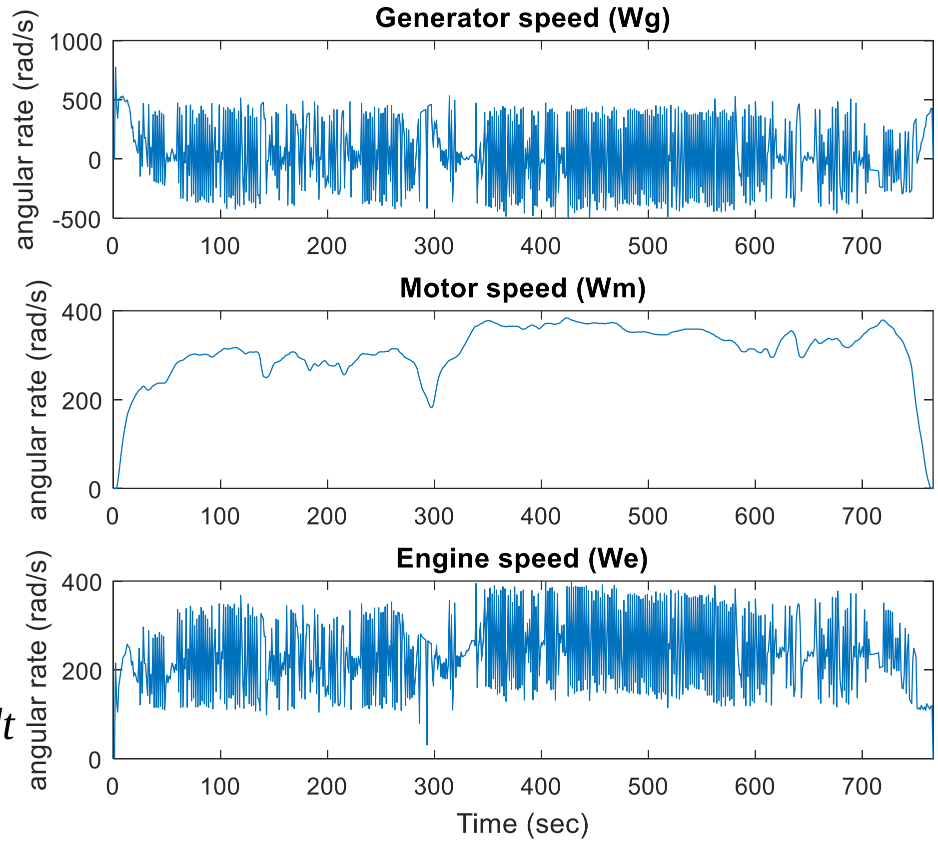
Additional Features from Speed Profiles



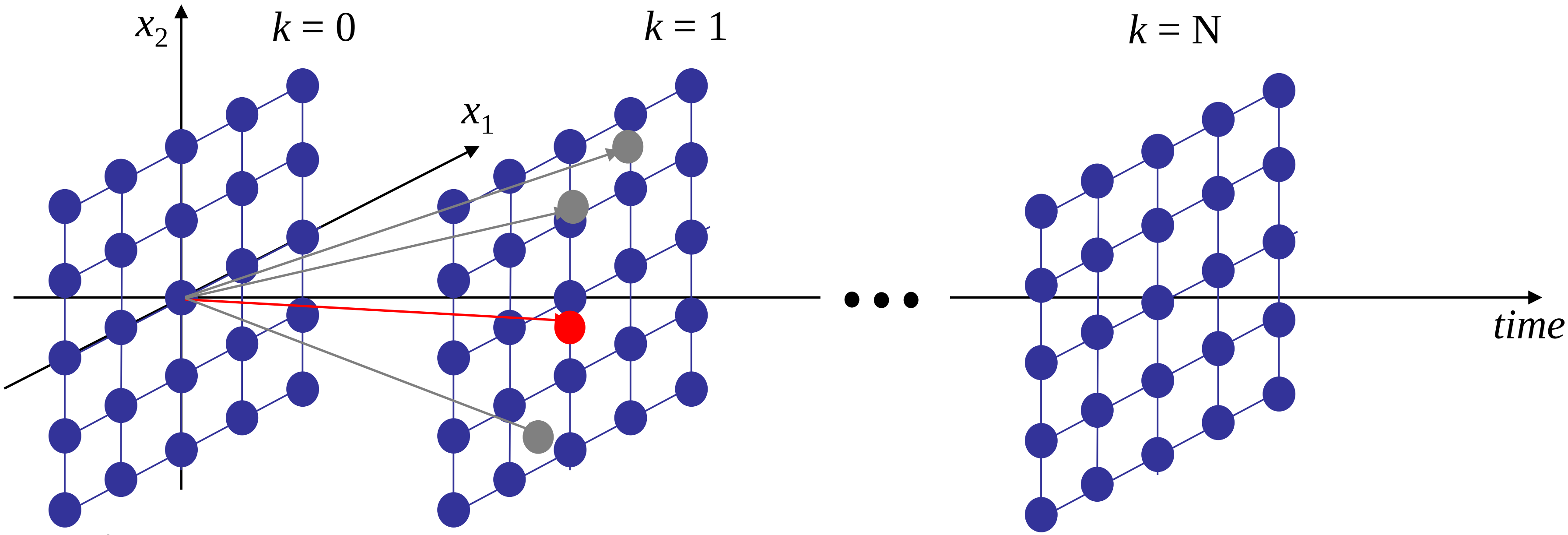
$$W_{g[k]} = \frac{W_{e[k]} \cdot (R+S) + W_{v[k]} \cdot K_{FR} \cdot (-R)}{S}$$

$$W_{m[k]} = W_{v[k]} \cdot K_{FR}$$

$$W_{e[k]} = W_{e[k-1]} + \Big\{ T2W_{(1,1)} T_{e[k-1]} + T2W_{(1,2)} \left(T_{m+brake[k-1]} \cdot MR - T_{o[k-1]} \right) + T2W_{(1,3)} T_{g[k-1]} \Big\} dt$$



Dynamic Programming

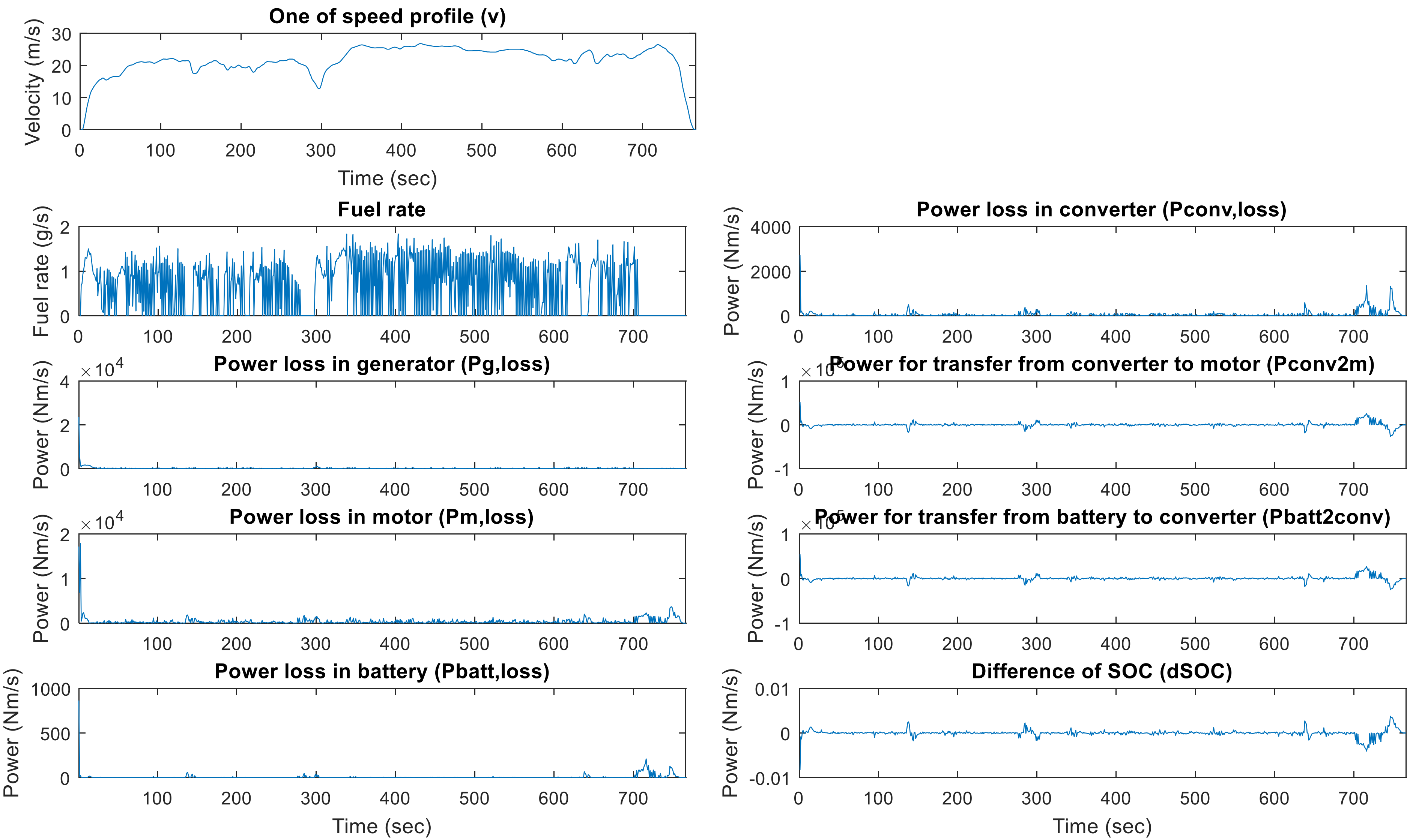


$$J_k^*(x_k) = \min_{u_{1,k}, u_{2,k}} [L(x_k, u_{1,k}, u_{2,k})] \qquad J_N^* = \alpha(SOC_N - SOC_{ref})^2$$

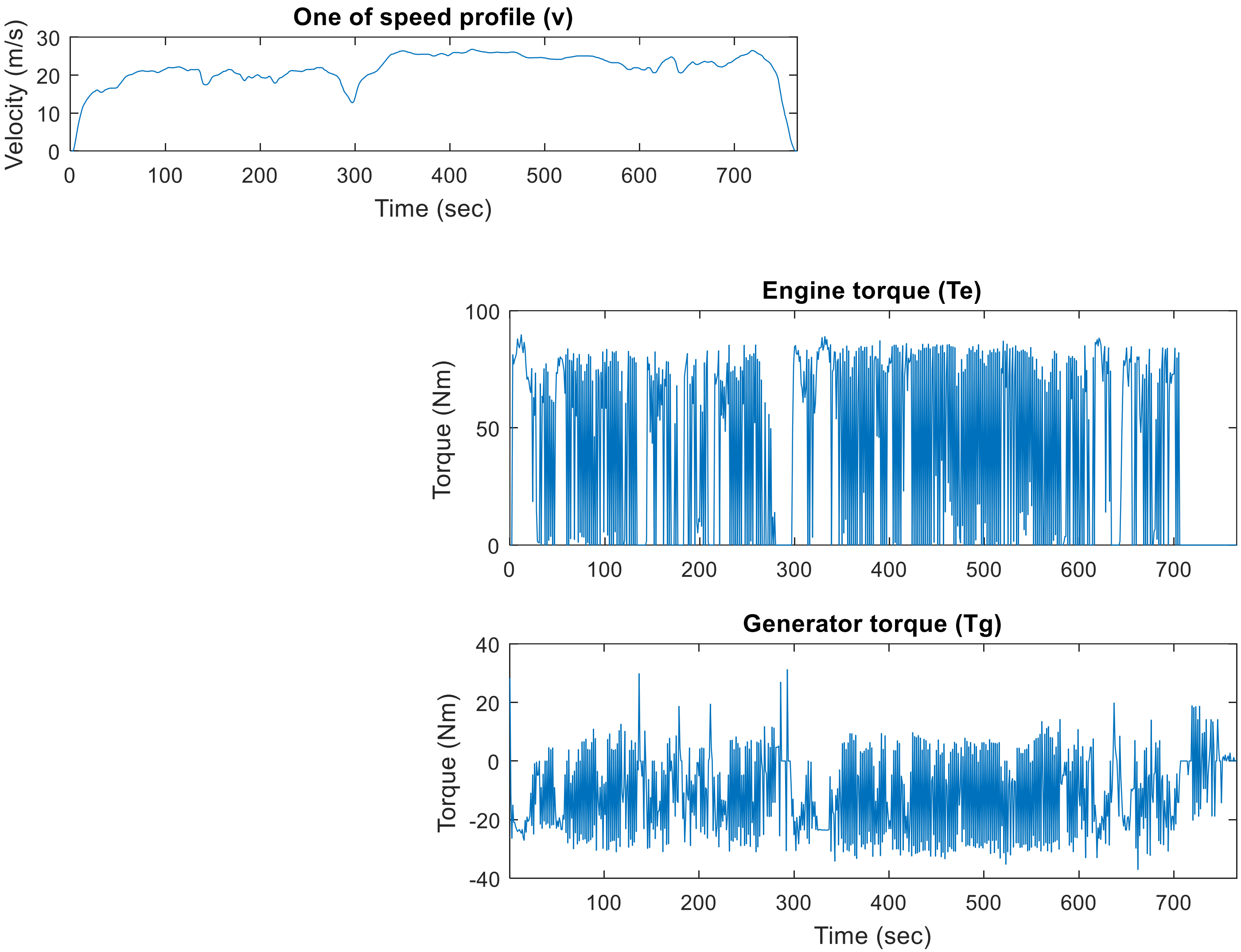
$$\text{minimize } J = \sum_{k=0}^{N-1} [J_k^*(x_k)] + J_N^*$$

State variables	Engine speed (W_e) SOC	Constraints	$0 \le w_e\ (x_1) \le 4000rpm$ $0.4 \le SOC(x_2) \le 0.7$ $-55 \le T_{mg1}\ (u_1) \le 55Nm$ $0 \le T_e\ (u_2) \le 100Nm$
Control inputs	Engine torque (T_e) Generator torque (T_{mg1})		

Additional Features from DP



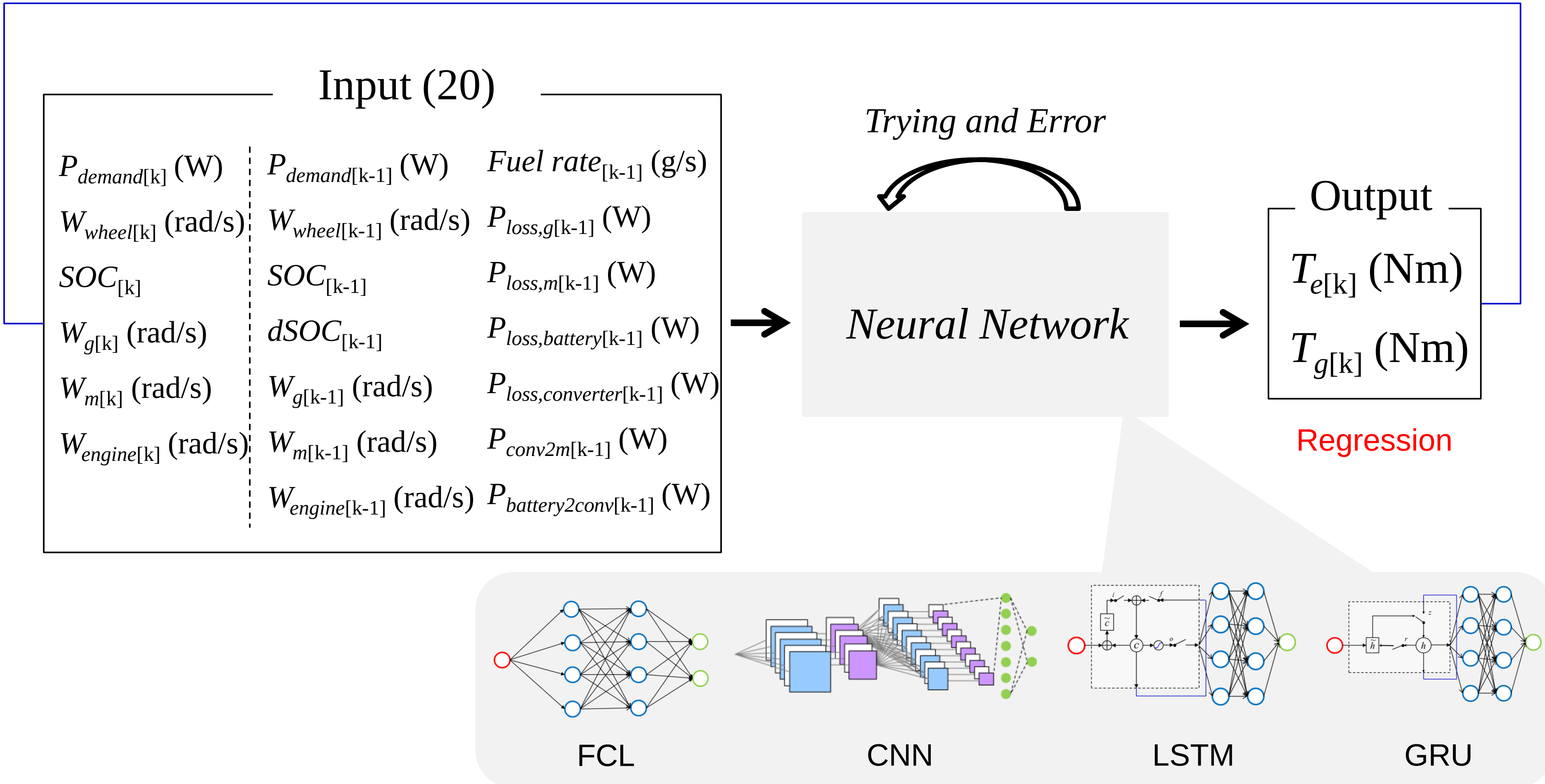
Output from DP



Supervised Learning

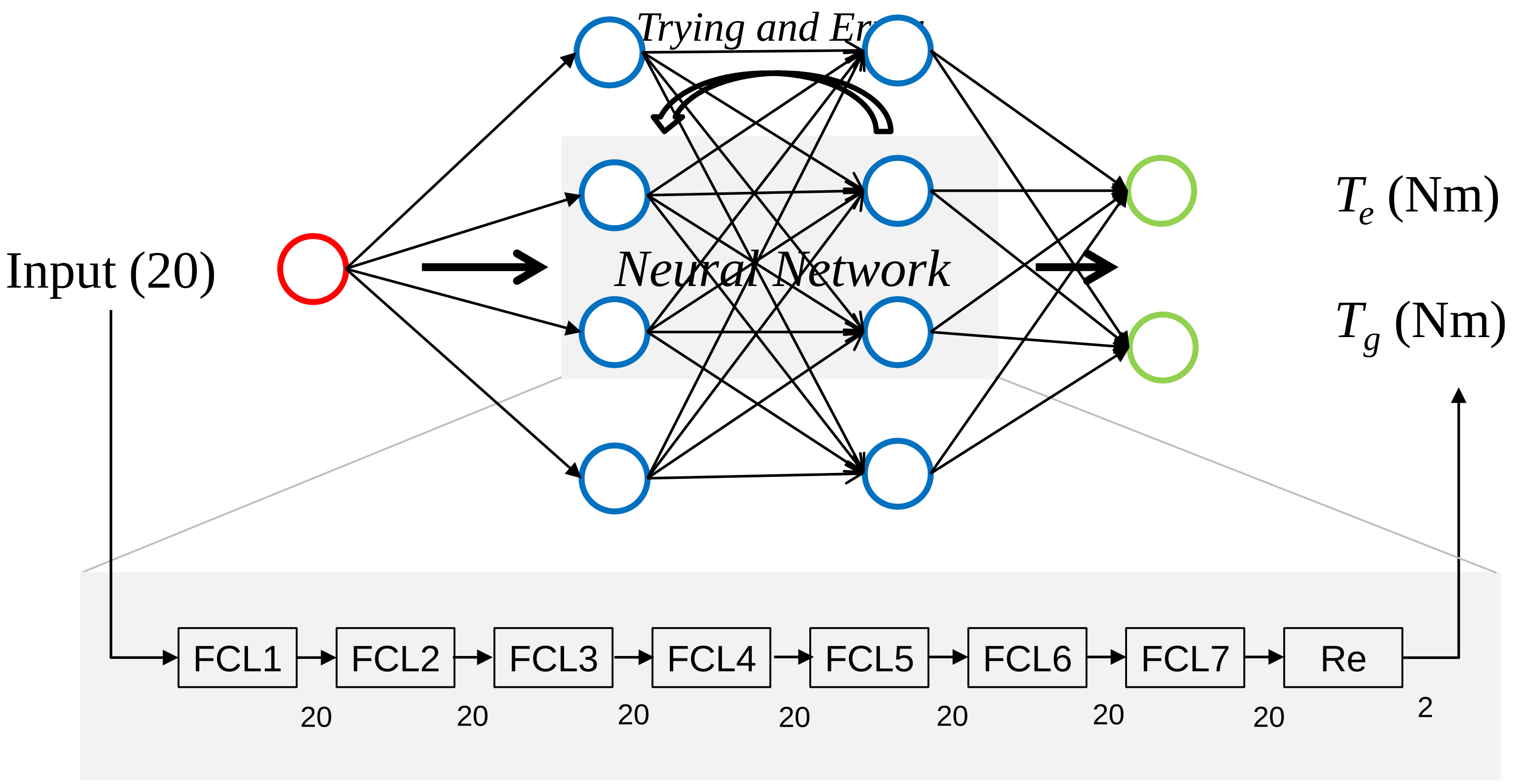
Supervised Learning:
Problem Definition

- T_e/T_g prediction with various DNN structures (Regression problem)

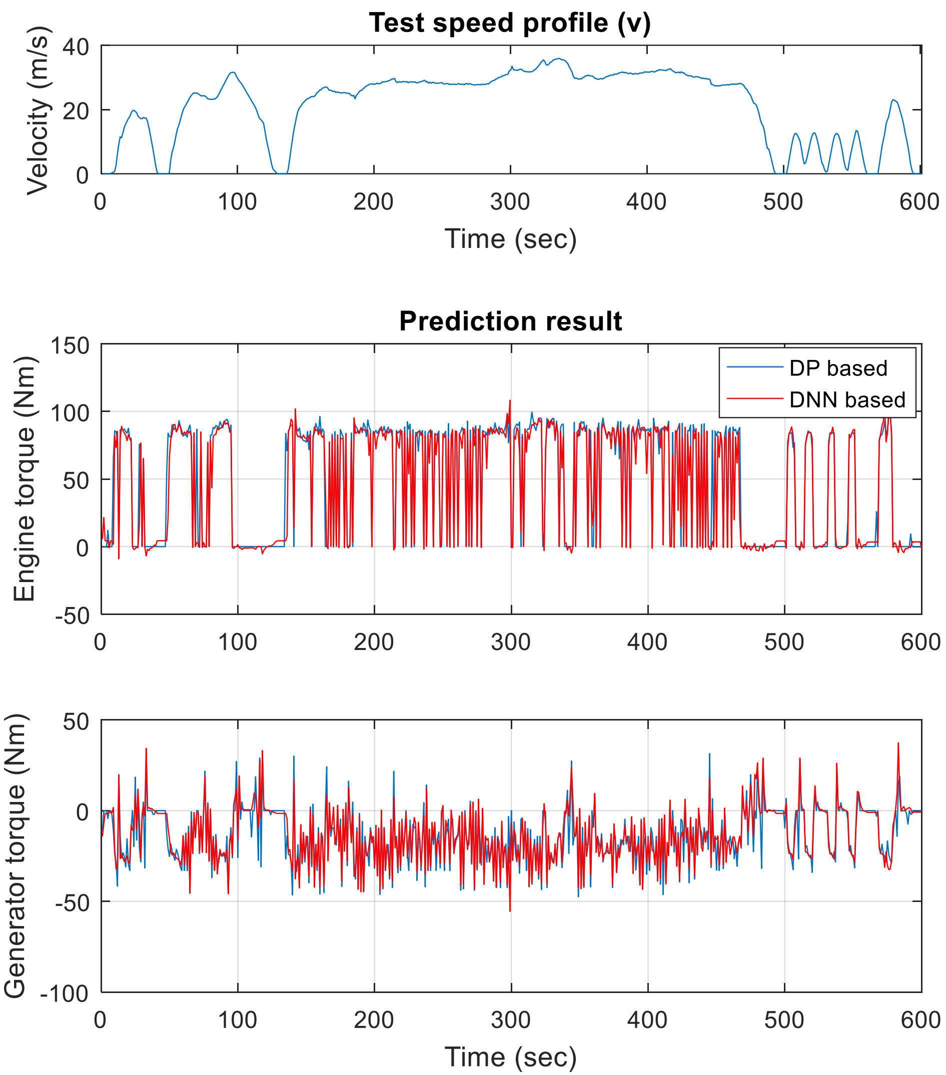


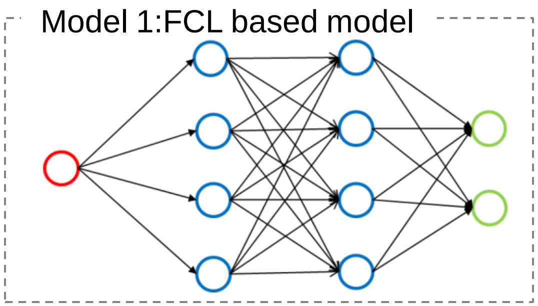
Supervised Learning:
Designed Model 1 (Based on FCL)

- Directly regression model with fully-connected layer



Supervised Learning:
Prediction Result for Model 1



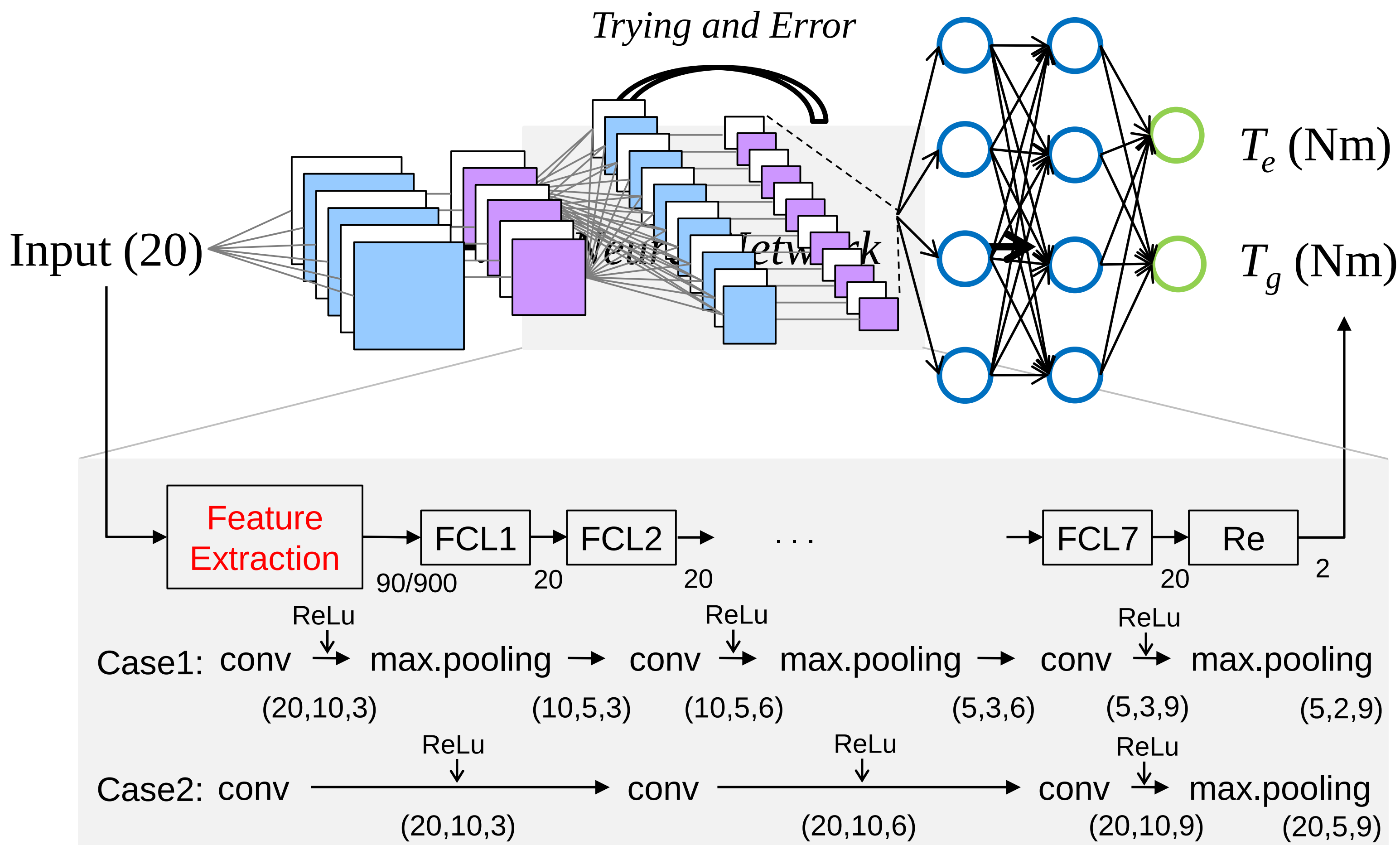


RMSE	Train result	Test result (US06)
Te	9.6292	12.3085
Tg	3.6647	5.8915

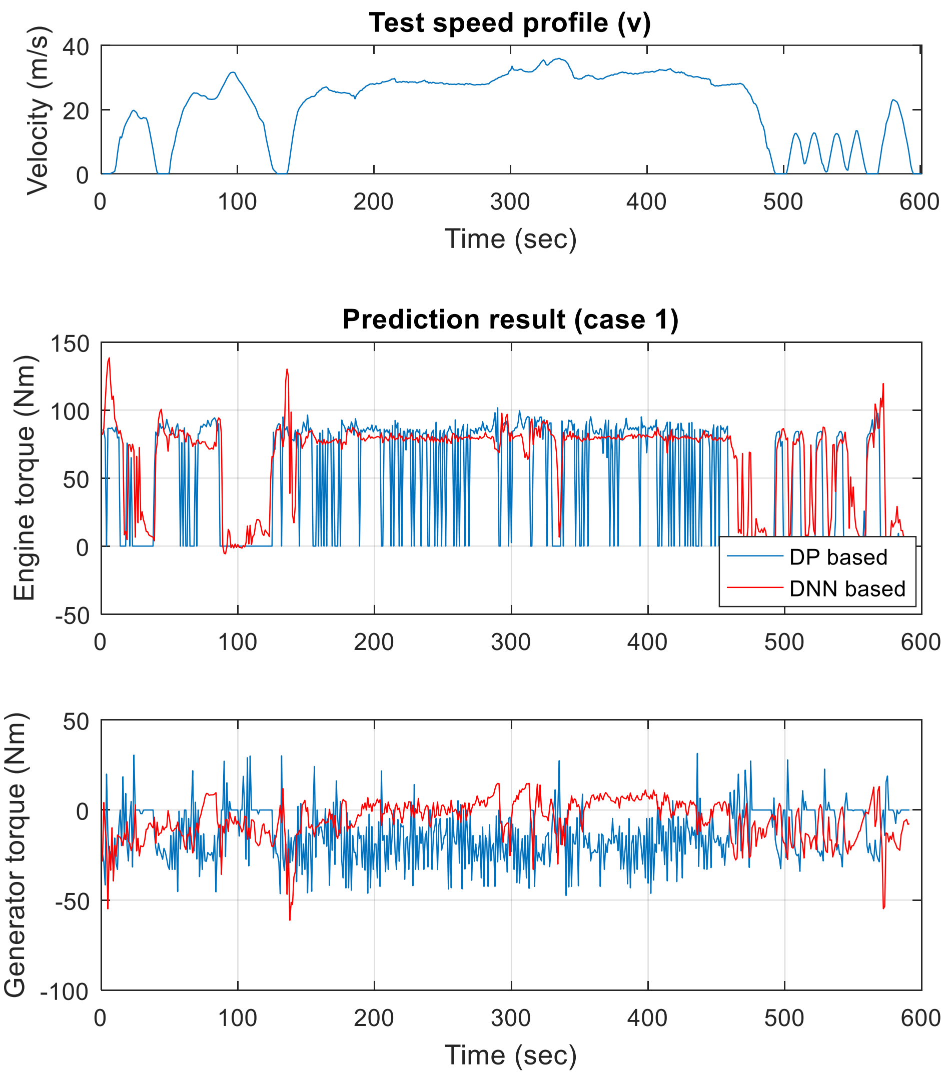
Supervised Learning:
Designed Model 2 (Based on CNN)

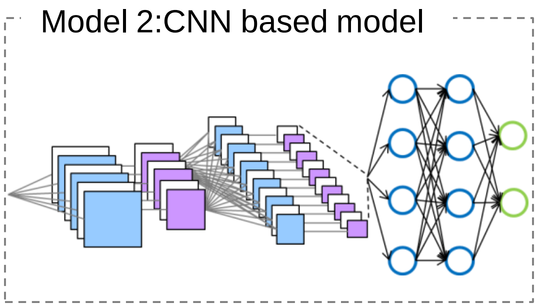
- Directly regression model with CNN

Time window = 10 steps



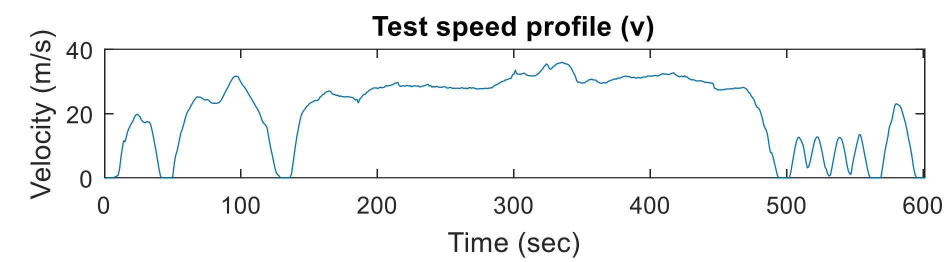
Supervised Learning:
Prediction Result for Model 2 (Case 1)

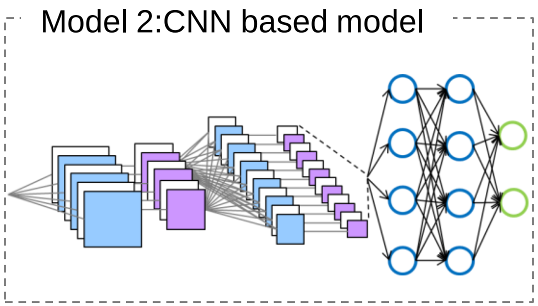


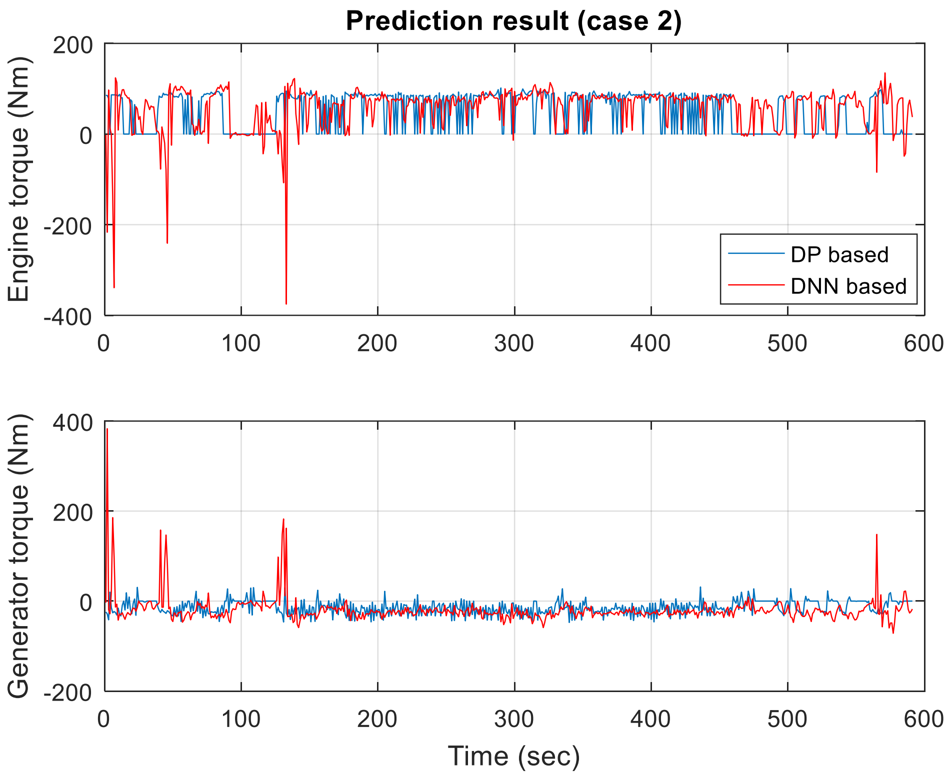


RMSE	Train result	Test result (US06)
Te	43.3254	39.3080
Tg	16.3033	24.0154

Supervised Learning:
Prediction Result for Model 2 (Case 2)



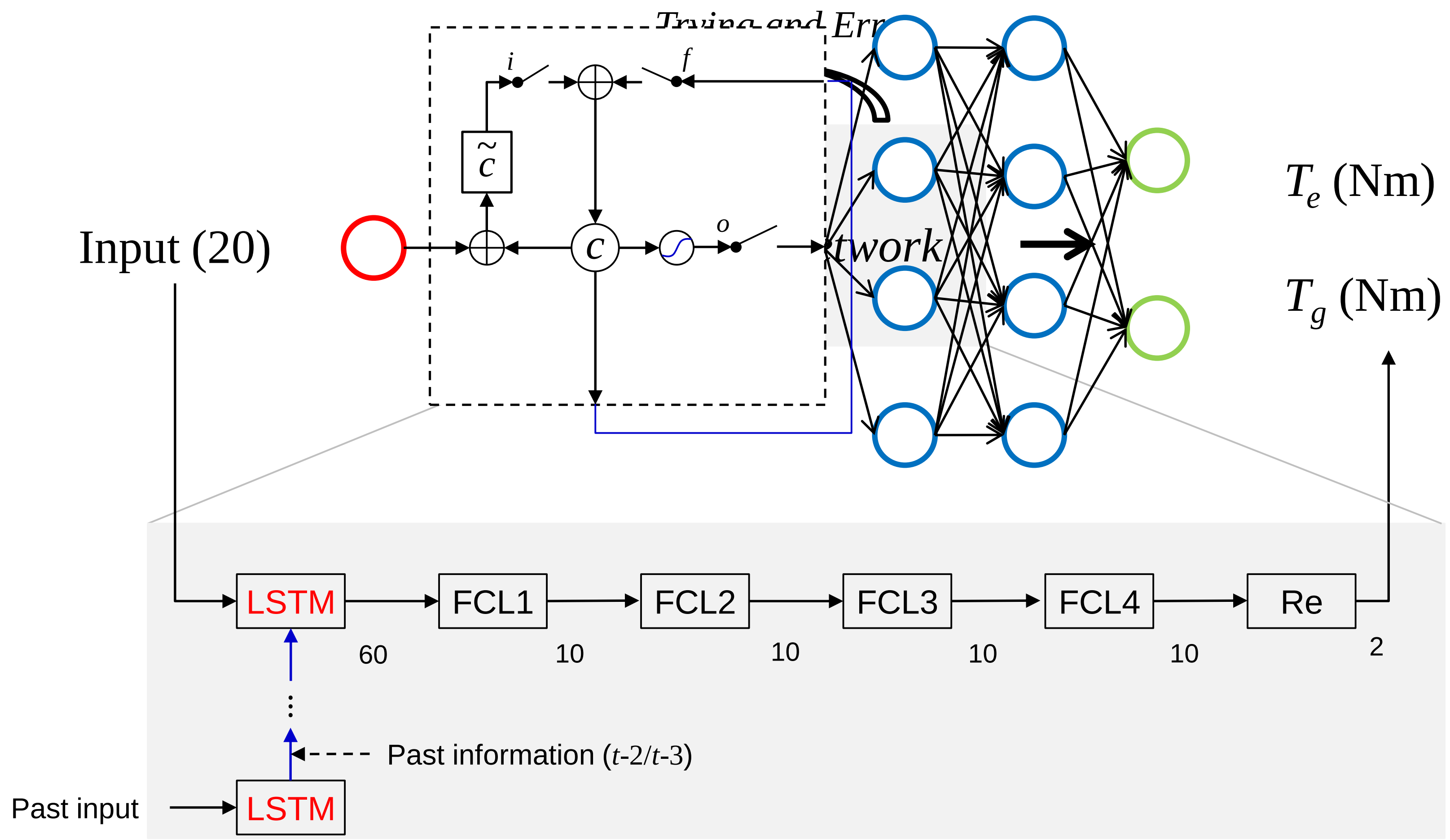




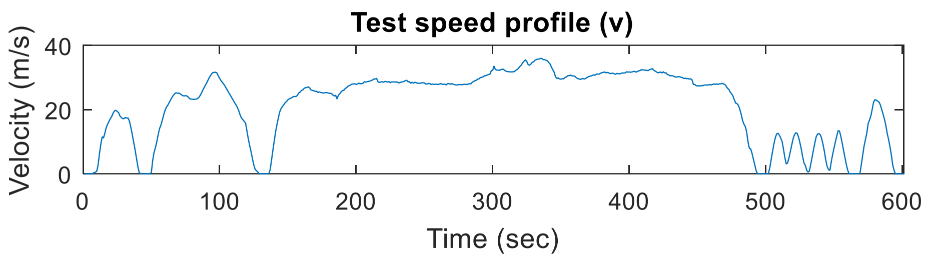
RMSE	Train result	Test result (US06)
Te	44.1325	62.1841
Tg	22.5541	35.5008

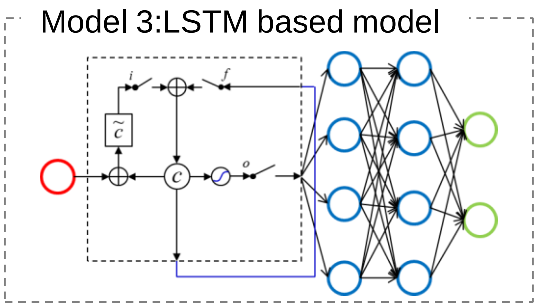
Supervised Learning:
Designed Model 3 (Based on LSTM)

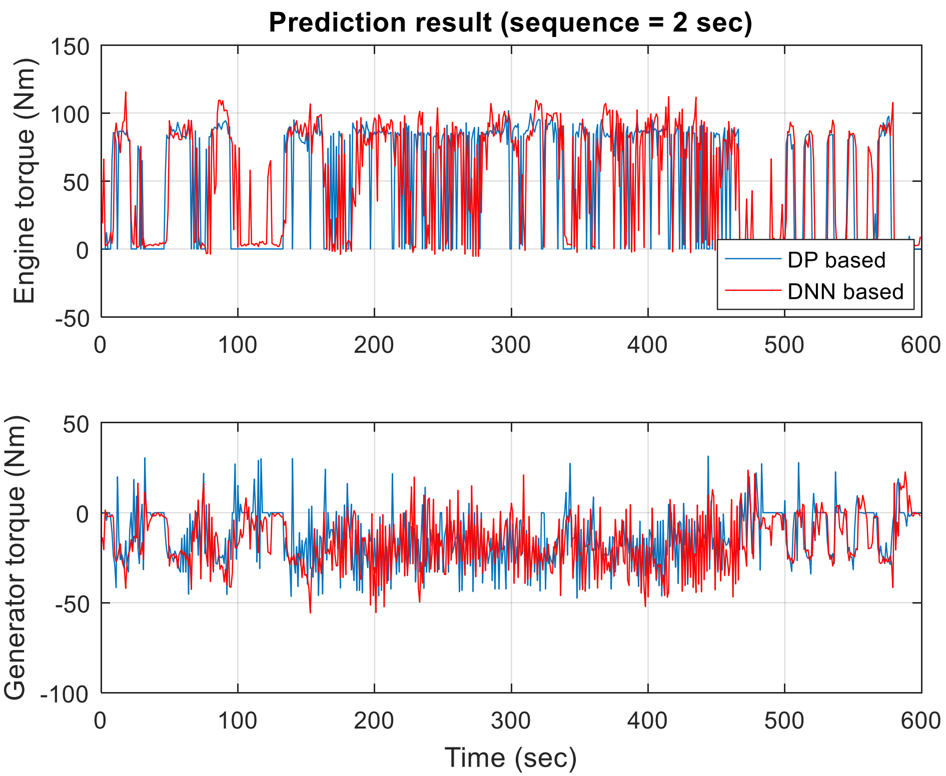
- Directly regression model with LSTM



Supervised Learning:
Prediction Result for Model 3 (Sequence = 2 sec)

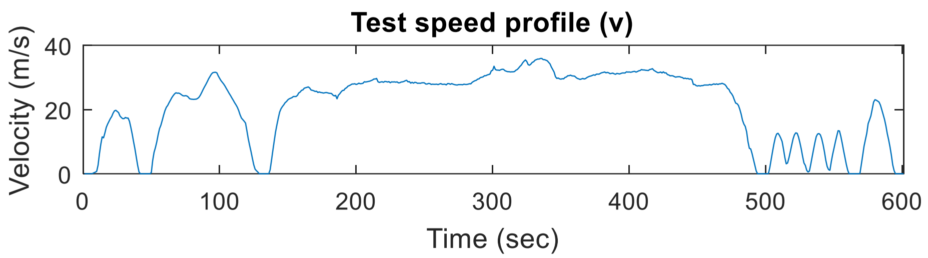


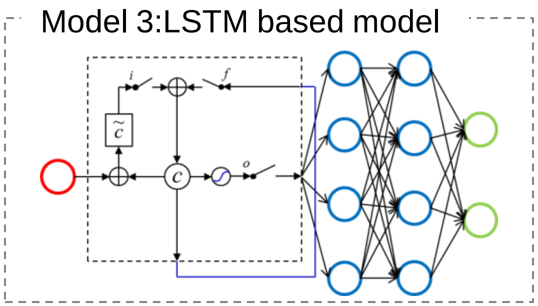


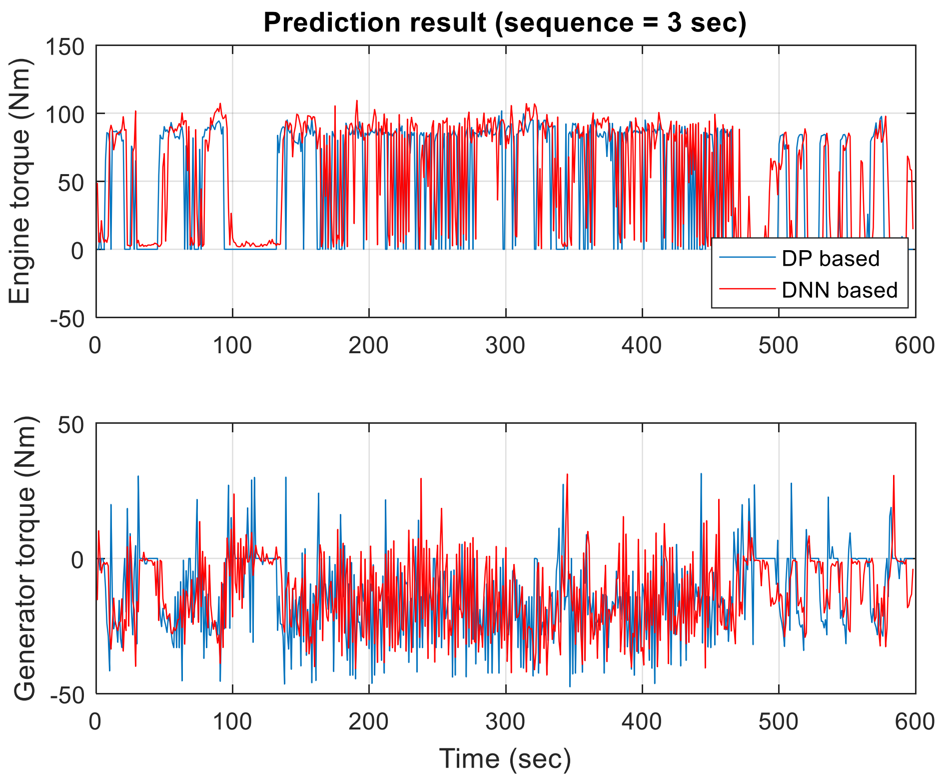


RMSE	Train result	Test result (US06)
Te	31.9129	39.2727
Tg	11.2593	15.7211

Supervised Learning:
Prediction Result for Model 3 (Sequence = 3 sec)







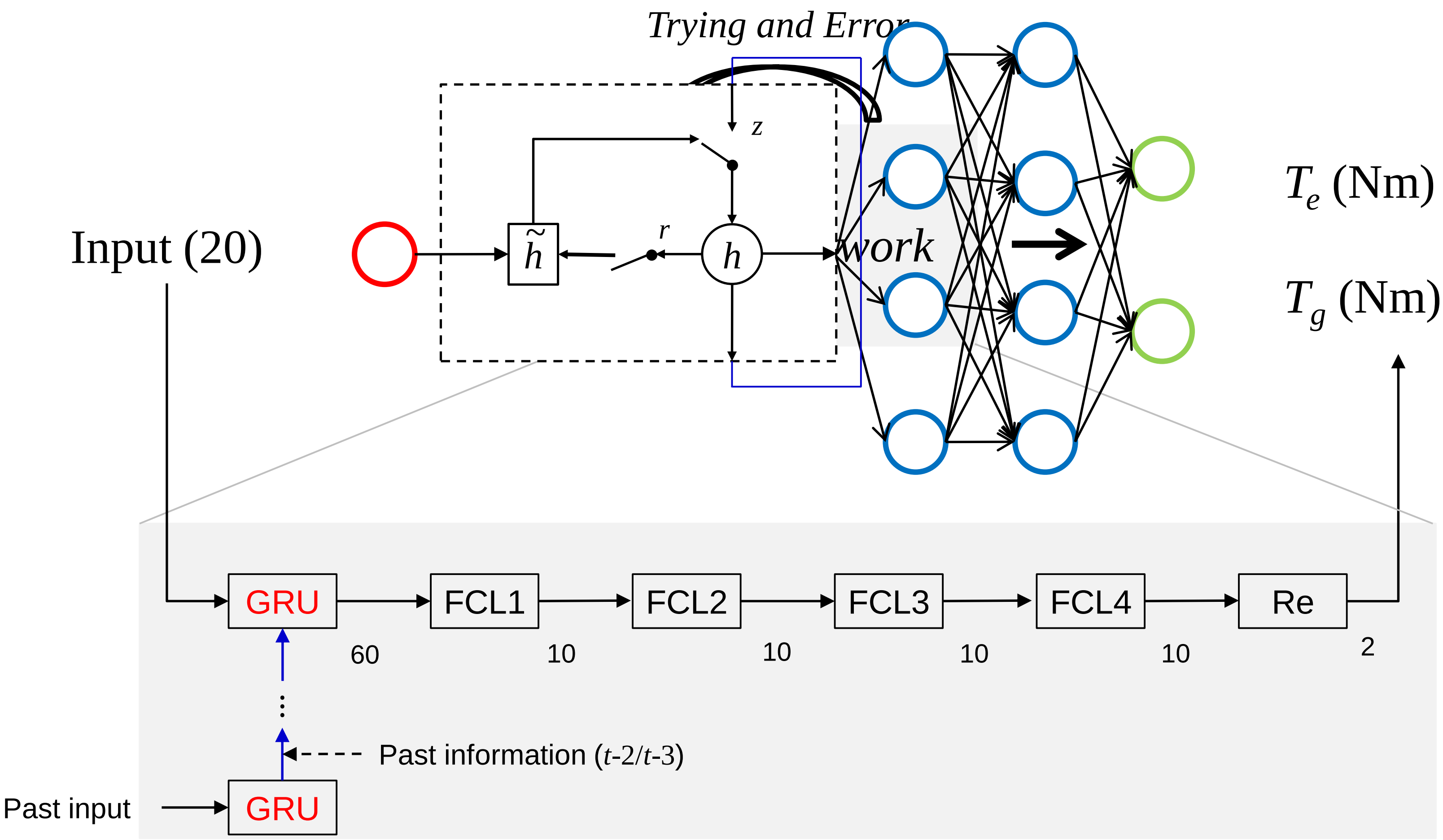
RMSE	Train result	Test result (US06)
Te	32.7164	43.1871
Tg	11.0311	16.4077

➔ Sequence ↑ → accuracy ↓

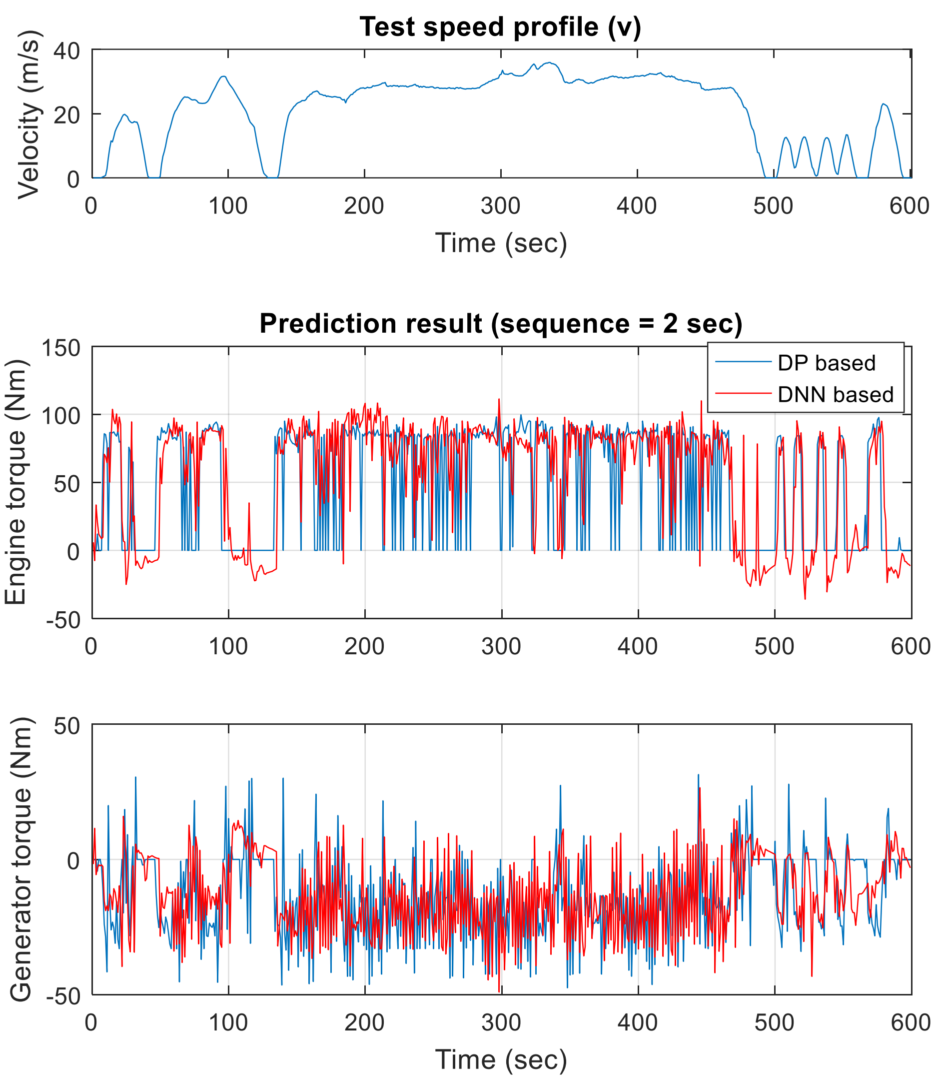
(No time series feature in database)

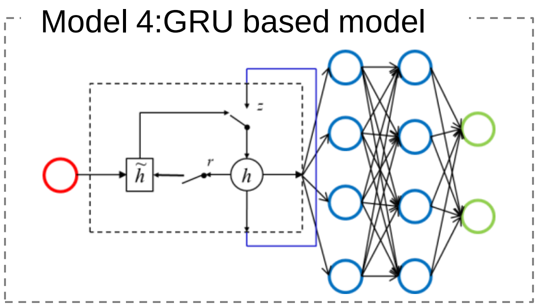
Supervised Learning:
Designed Model 4 (Based on GRU)

- Directly regression model with GRU



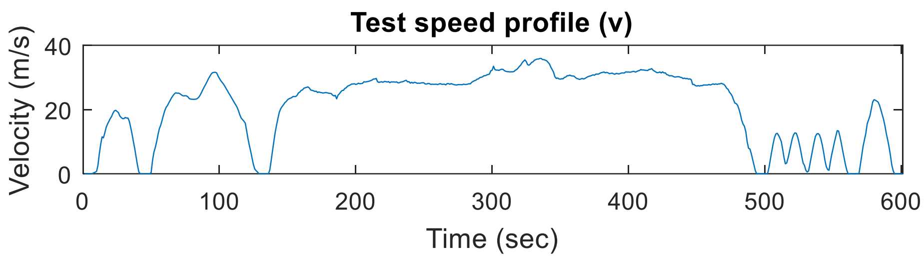
Supervised Learning:
Prediction Result for Model 4 (Sequence = 2 sec)

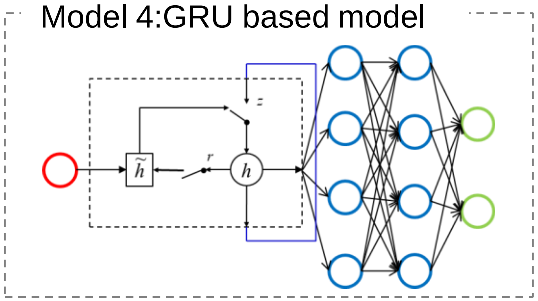


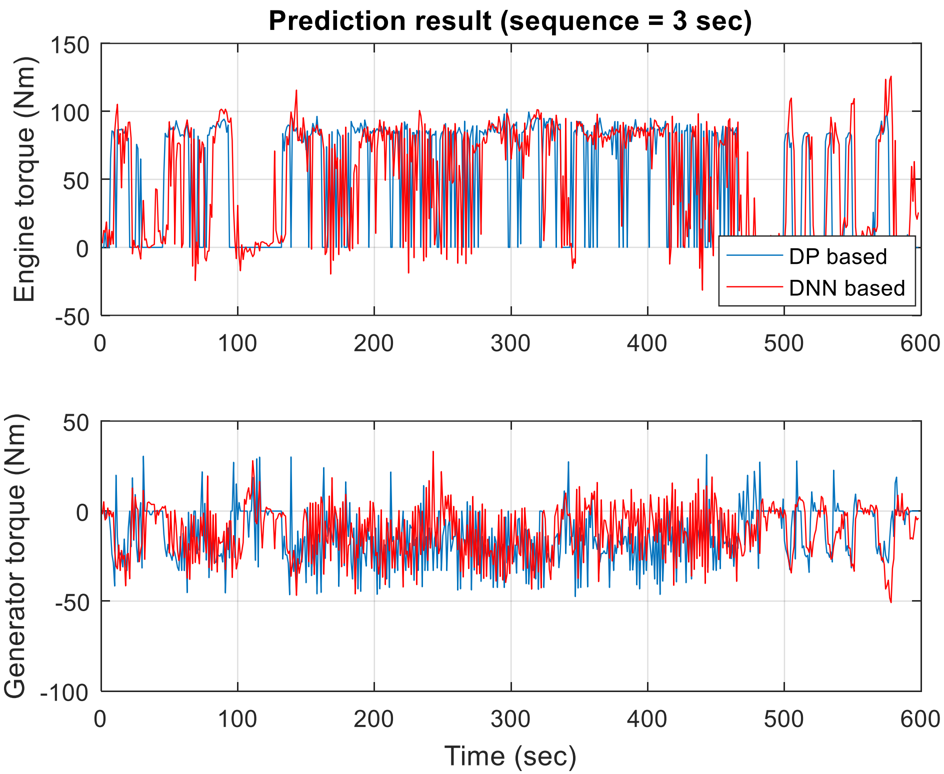


RMSE	Train result	Test result (US06)
Te	29.2779	35.8741
Tg	11.0861	14.7434

Supervised Learning:
Prediction Result for Model 4 (Sequence = 3 sec)





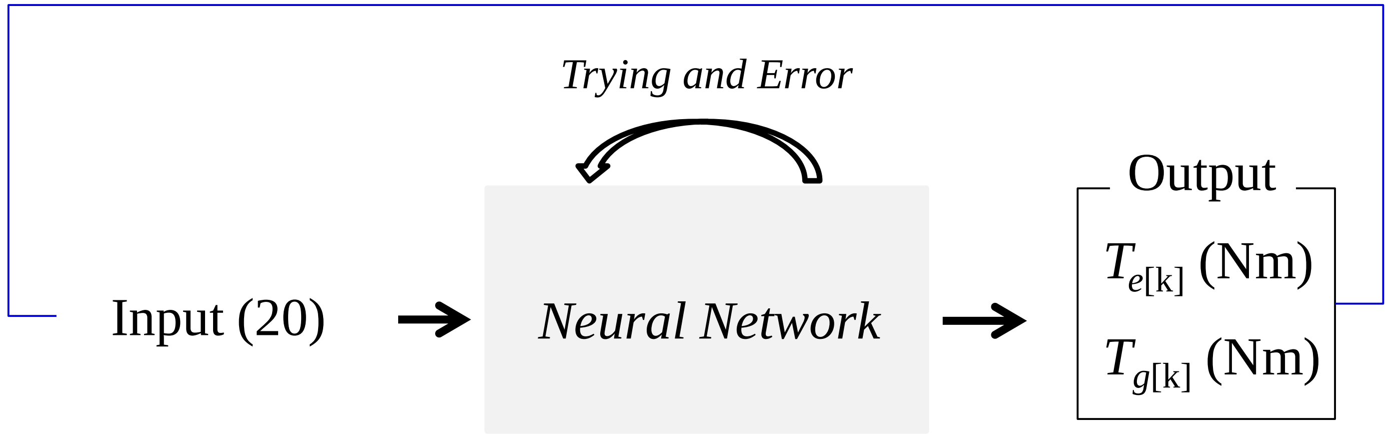


RMSE	Train result	Test result (US06)
Te	33.7160	42.5497
Tg	12.5286	17.8591

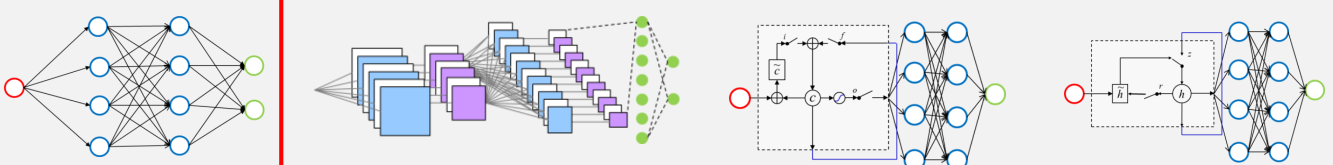
➔ Sequence ↑ → accuracy ↓

(No time series feature in database)

Supervised Learning:
Summary of 4 Models for Direct Output Prediction



Regression

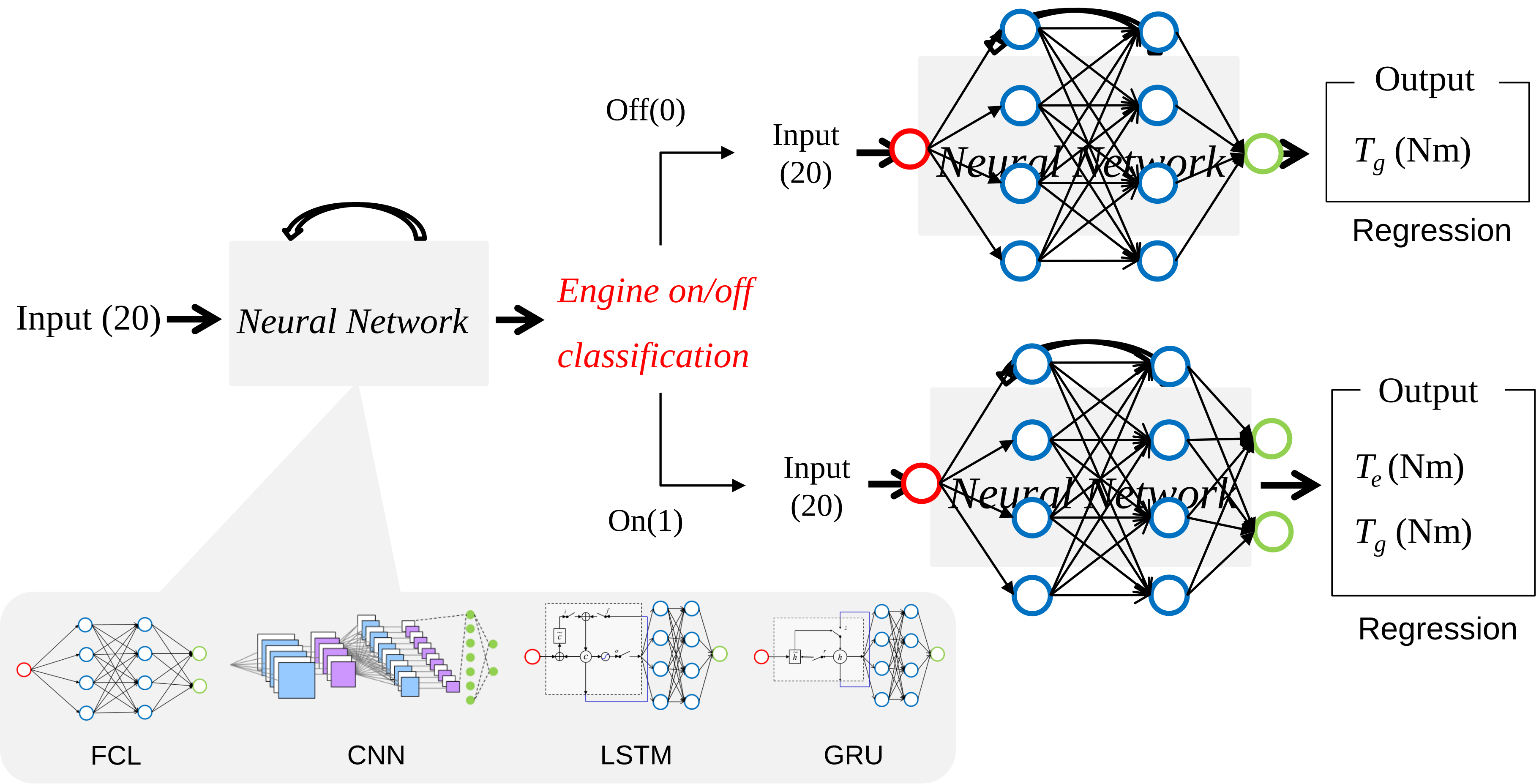


Lower RMSE for test data	FCL	CNN	LSTM	GRU
Error for T_e	12.3085	39.3080	39.2727	35.8741
Error for T_g	5.8915	24.0154	15.7211	14.7434

Best choice for regression

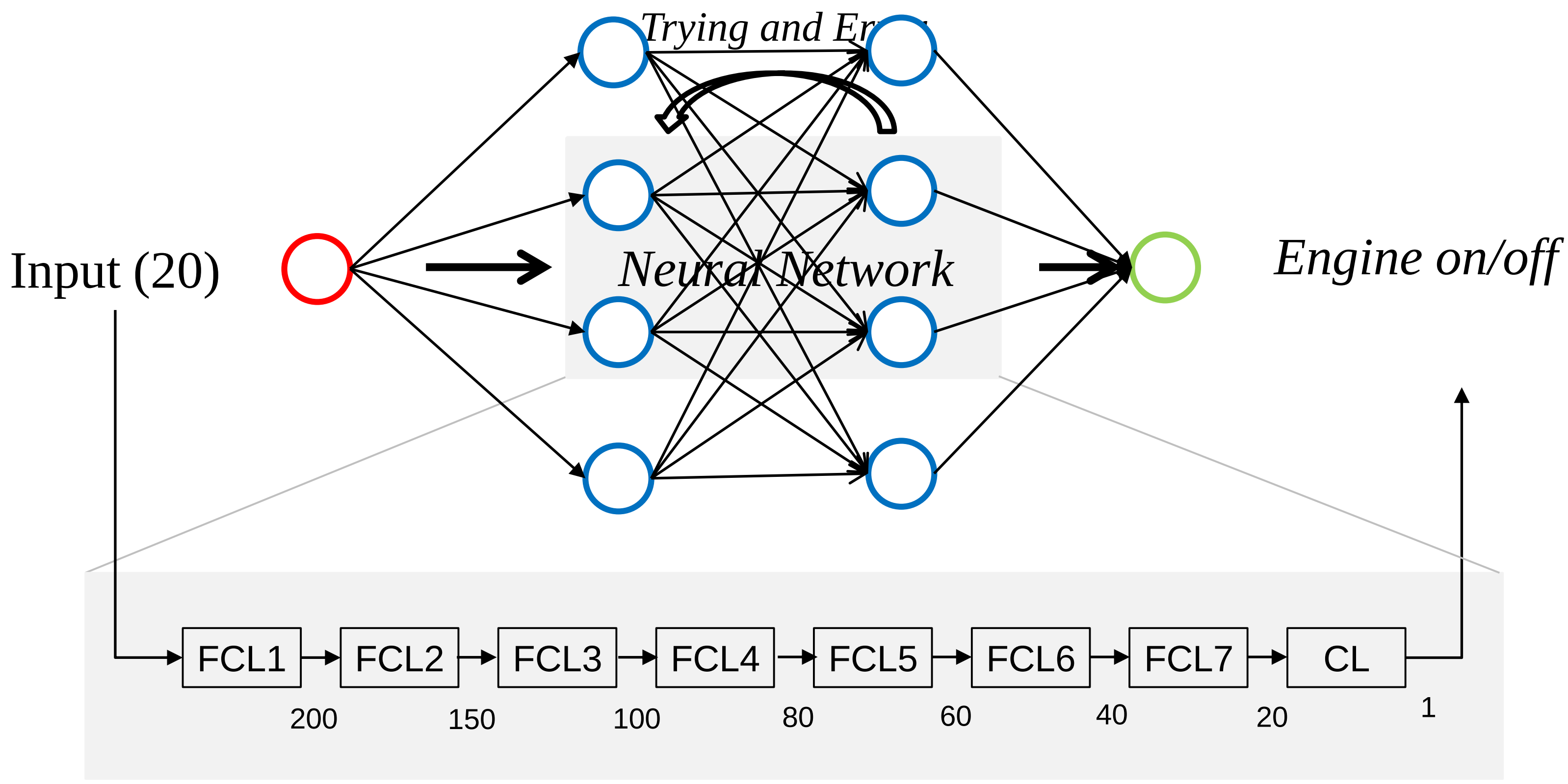
Supervised Learning:
New Approach with Classification of Engine Switching

- Engine switching prediction with various DNN structures (Classification)
  + T_e/T_g prediction with FCL structure

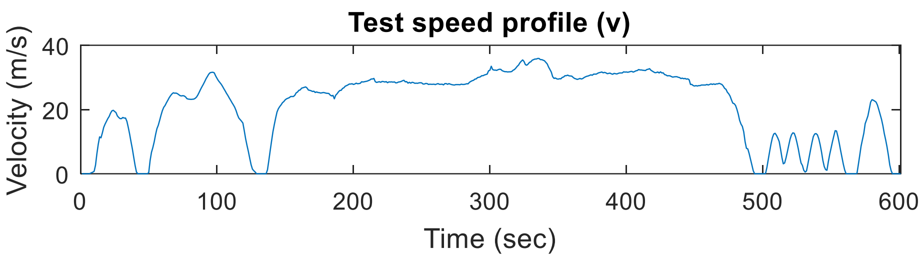


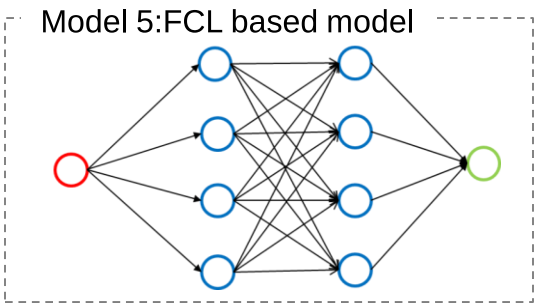
Supervised Learning:
Designed Model 5 (Based on FCL)

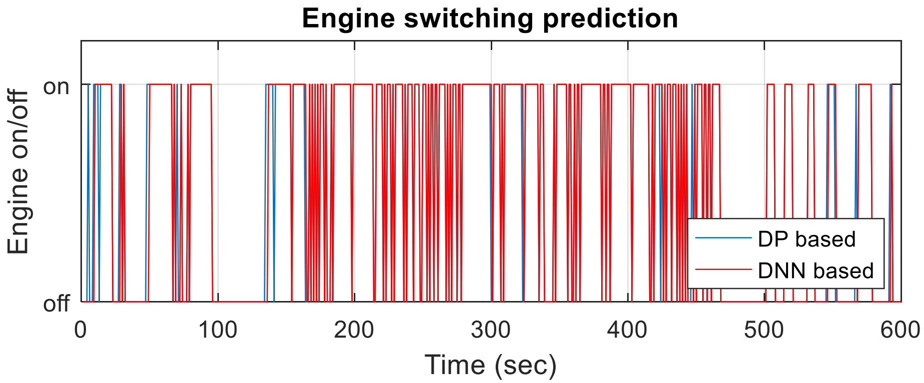
- Engine switching classification model with fully-connected layer



Supervised Learning:
Prediction Result for Model 5





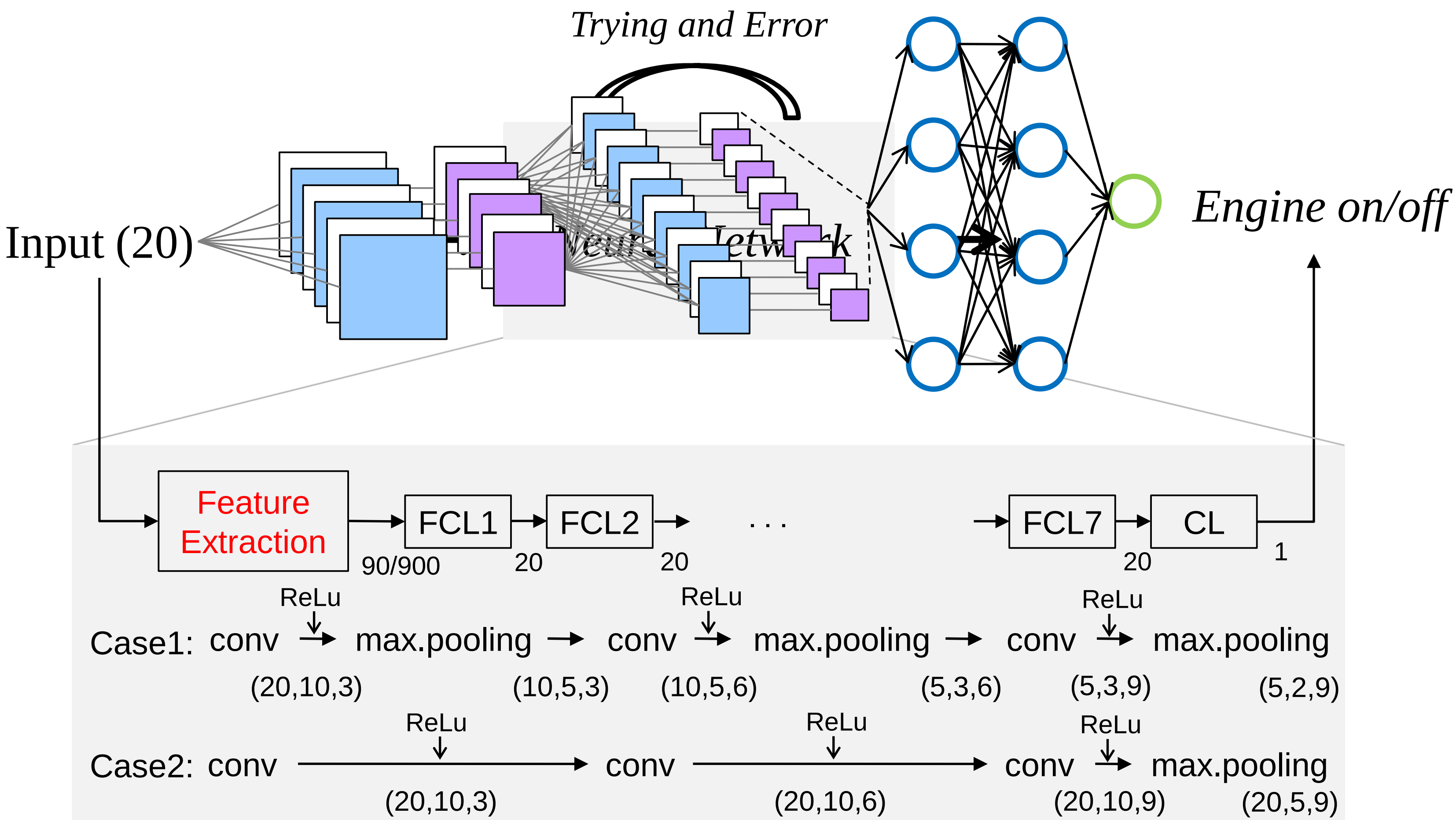


Accuracy (%)	Train result	Test result (US06)
No-Sequence	97.51	96.5

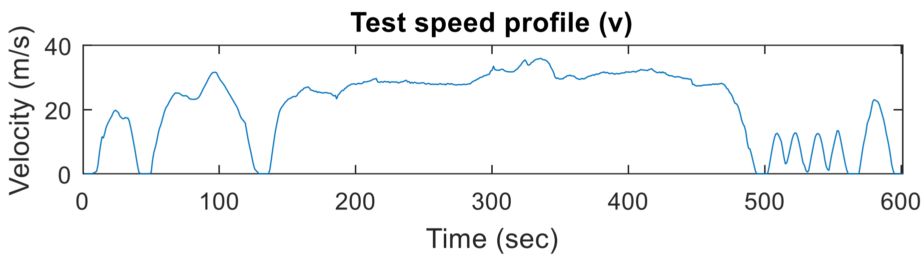
Supervised Learning:
Designed Model 6 (Based on CNN)

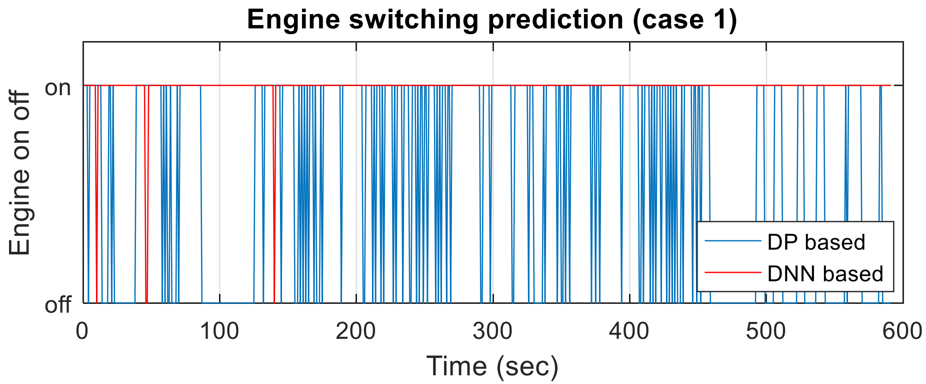
- Engine switching classification model with CNN

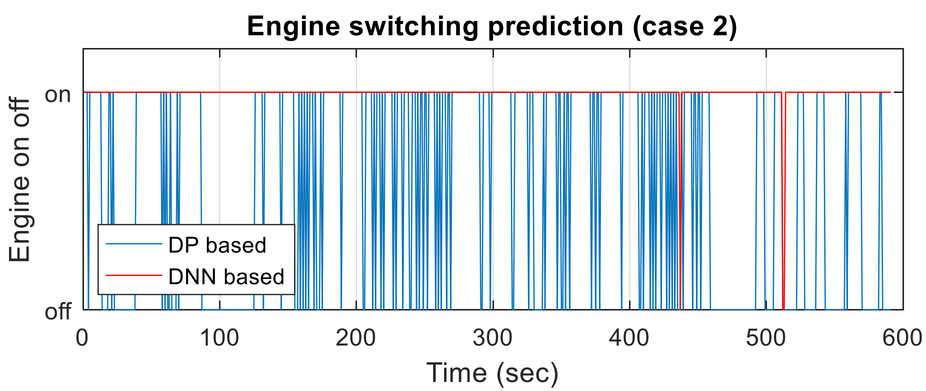
Time window = 10 steps

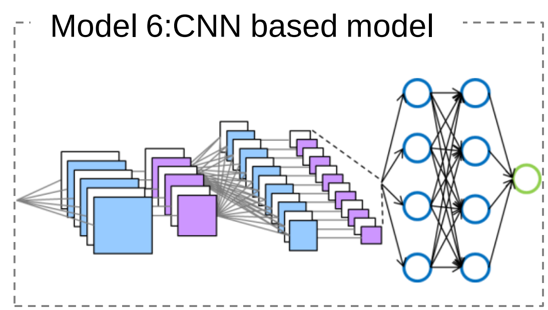


Supervised Learning:
Prediction Result for Model 6







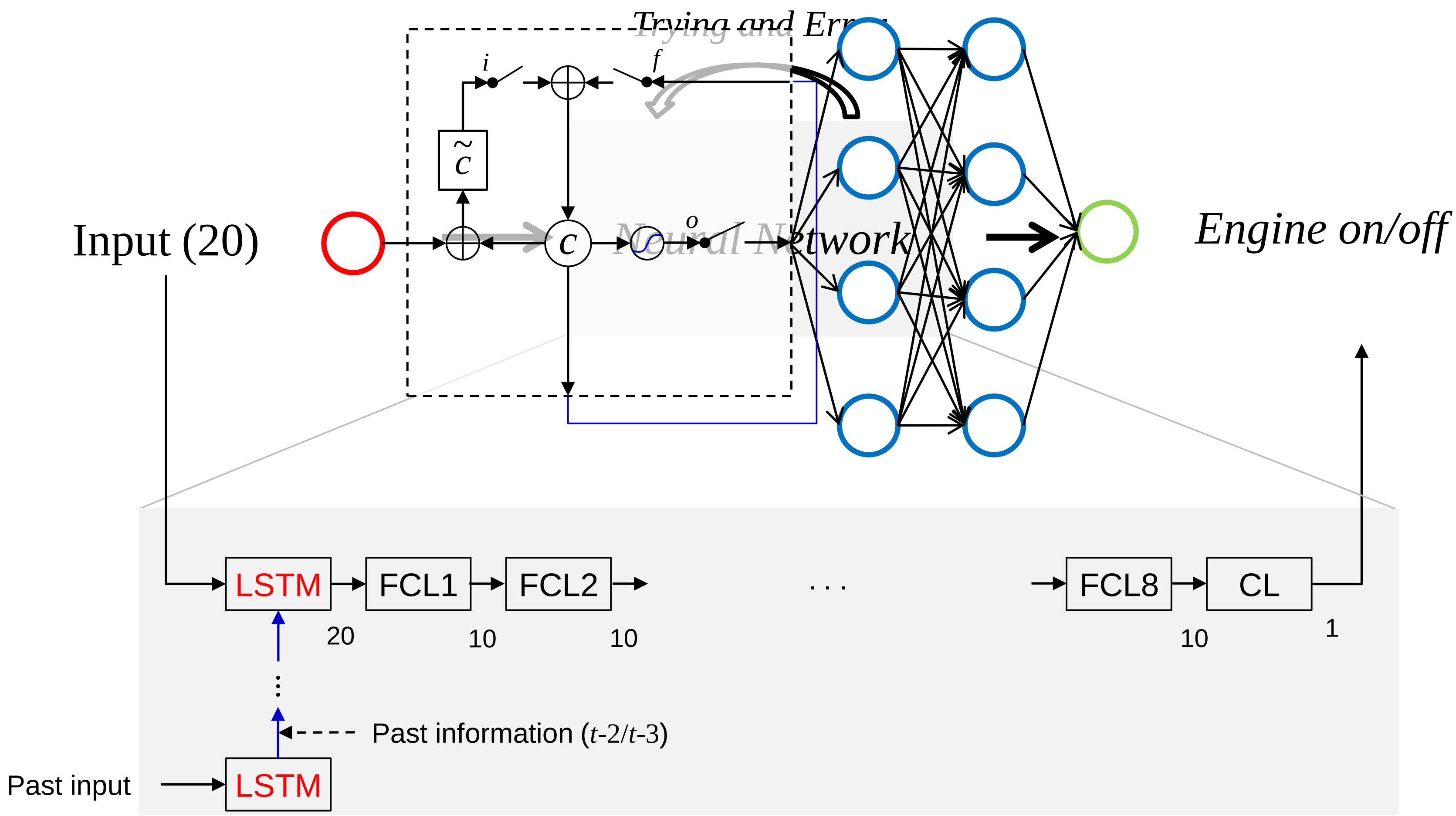


Accuracy (%)	Train result	Test result (US06)
Case1 (CPCPCP)	38.05	58.04
Case2 (CCCP)	38.05	59.22

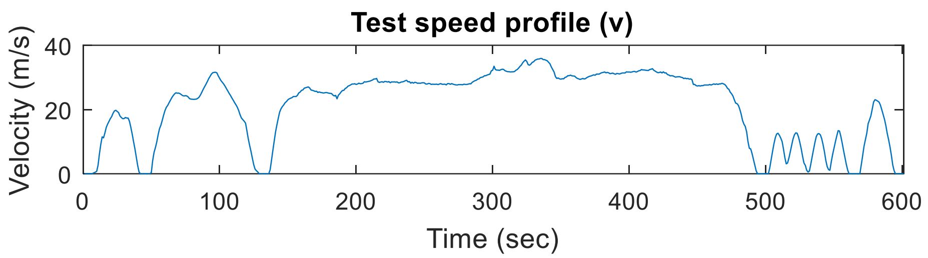
➔ CNN is not effective for this case

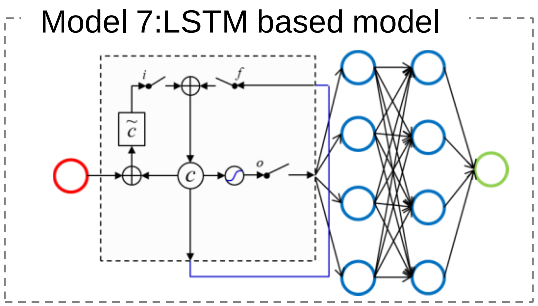
Supervised Learning:
Designed Model 7 (Based on LSTM)

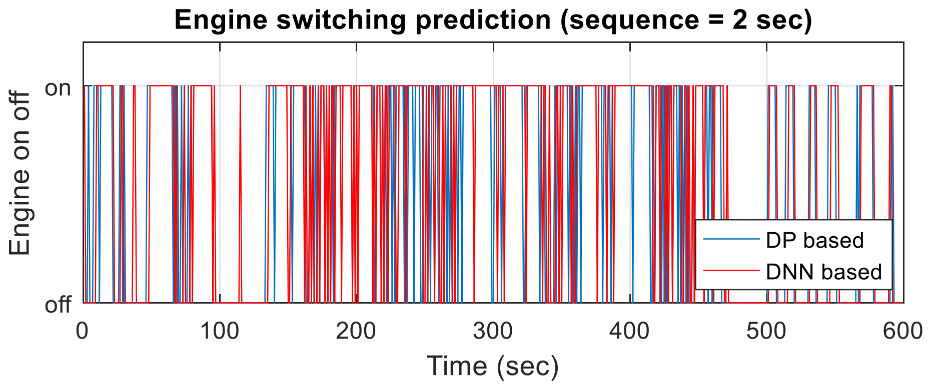
- Engine switching classification model with LSTM

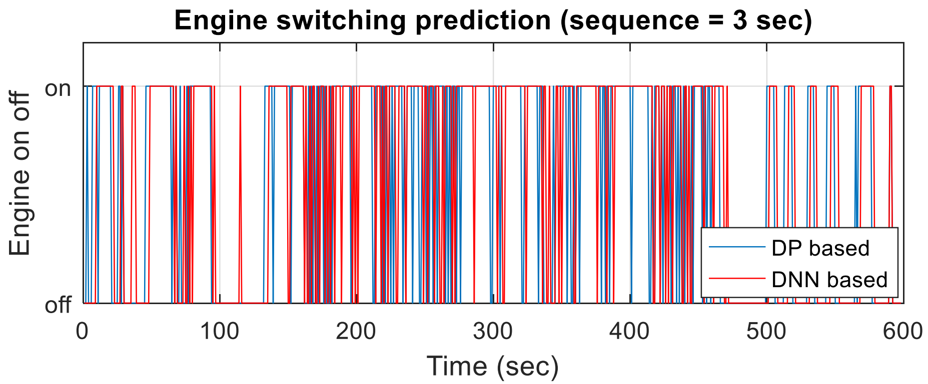


Supervised Learning:
Prediction Result for Model 7









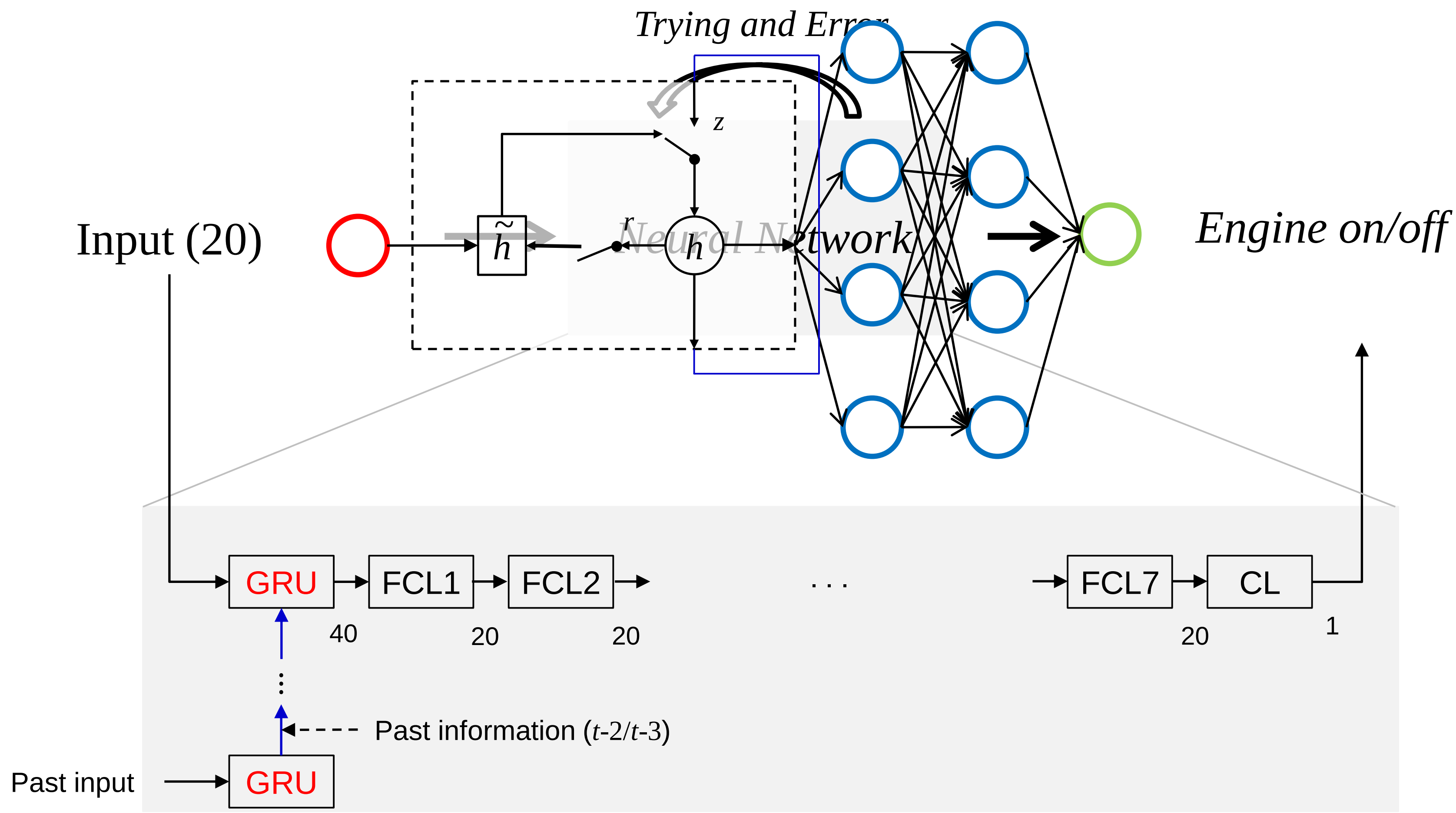
Accuracy (%)	Train result	Test result (US06)
Sequence =2steps	83.89	78.30
Sequence =3steps	68.18	72.74

➔ Sequence ↑ ➔ accuracy ↓

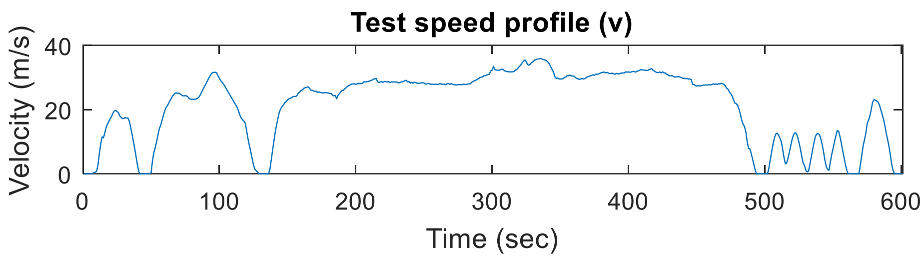
(No time series feature in database)

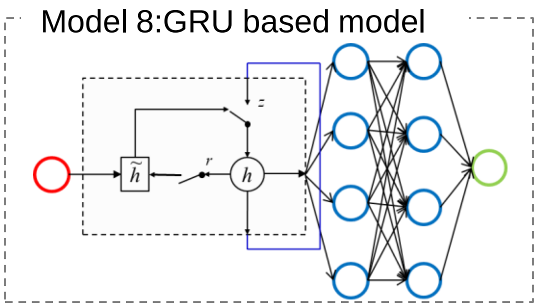
Supervised Learning:
Designed Model 8 (Based on GRU)

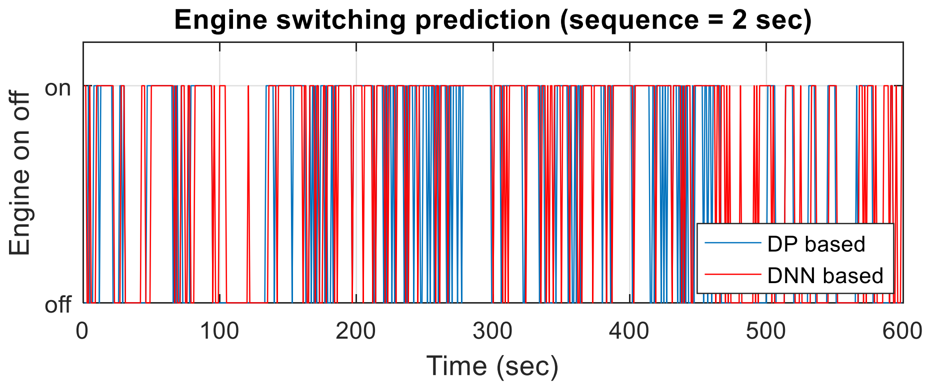
- Engine switching classification model with GRU



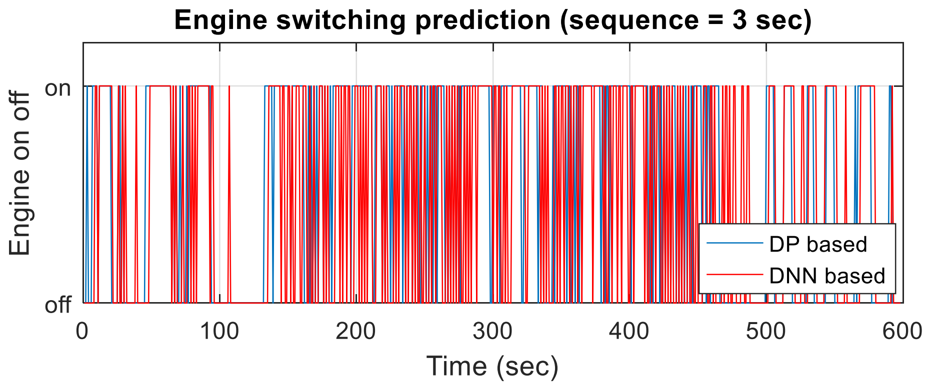
Supervised Learning:
Prediction Result for Model 8







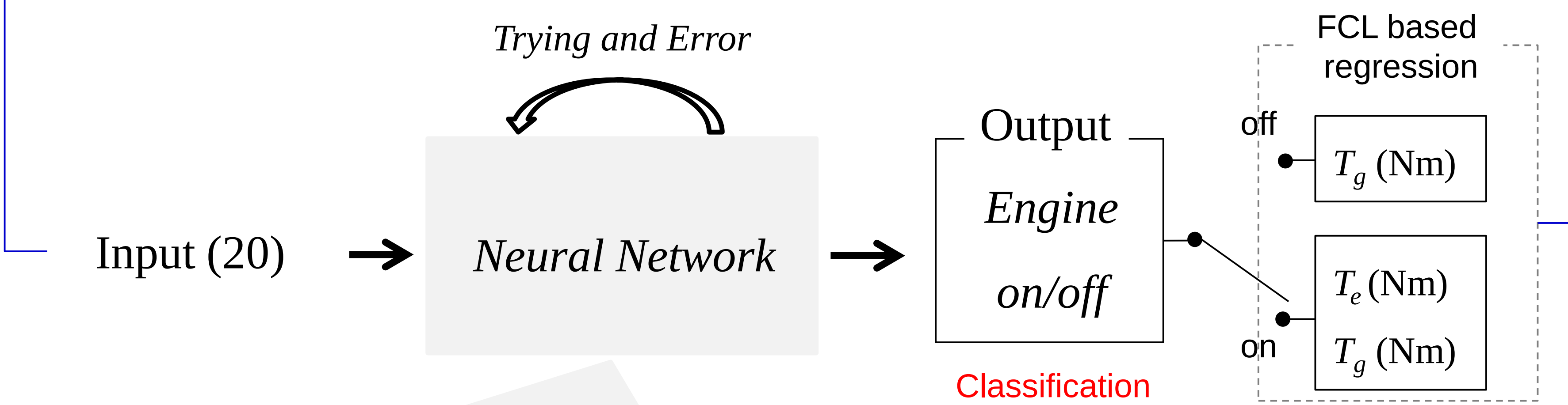
Accuracy (%)	Train result	Test result (US06)
Sequence =2steps	67.17	71.45
Sequence =3steps	76.68	68.90

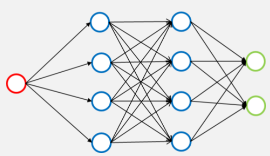
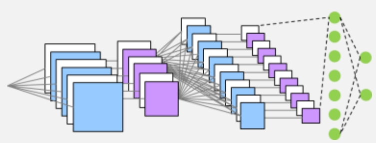
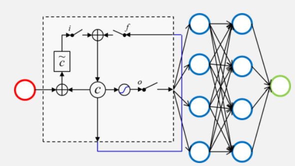
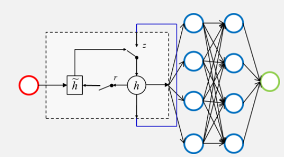


➔ Sequence ↑ ➔ accuracy ↓

(No time series feature in database)

Supervised Learning:
Summary of 4 Models for Engine Switching Prediction

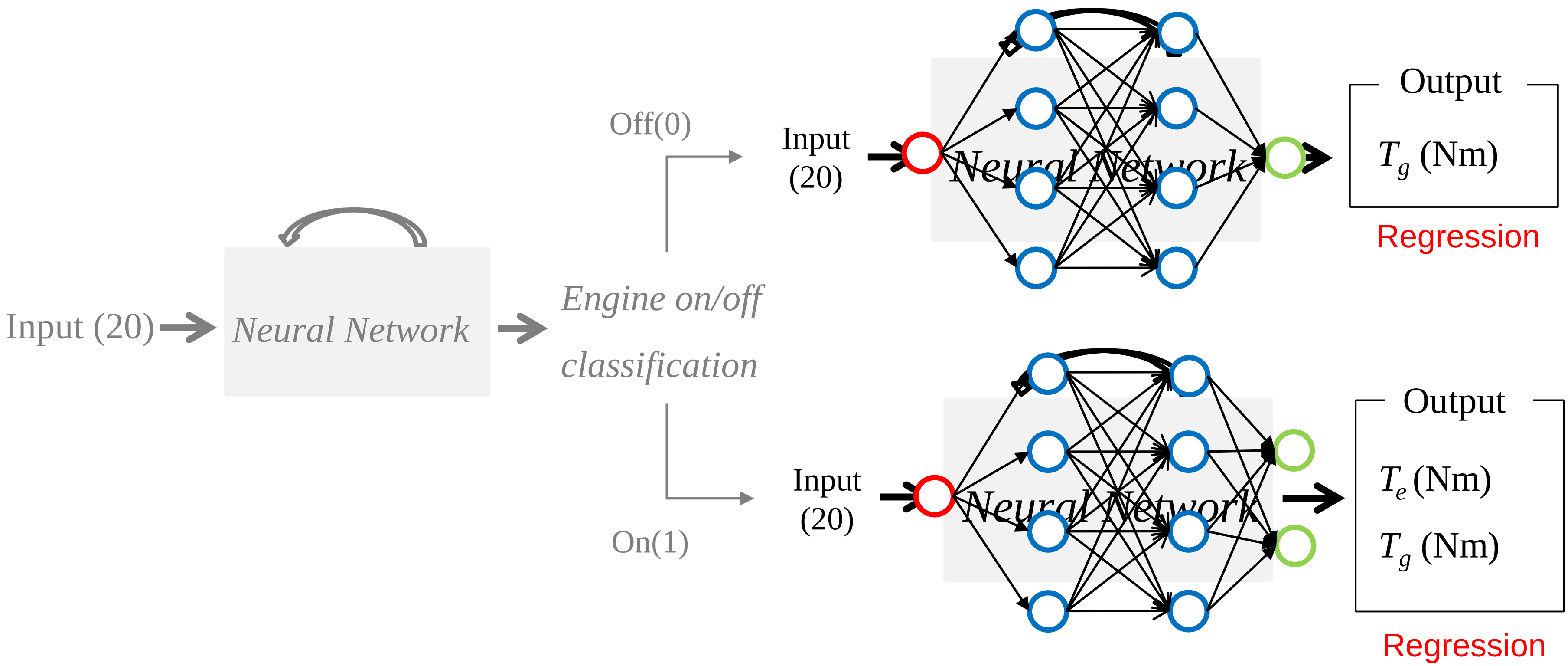


Higher accuracy for test data	 FCL	 CNN	 LSTM	 GRU
Accuracy for engine on/off	96.5%	59.22%	78.30%	71.45%

Best choice for classification

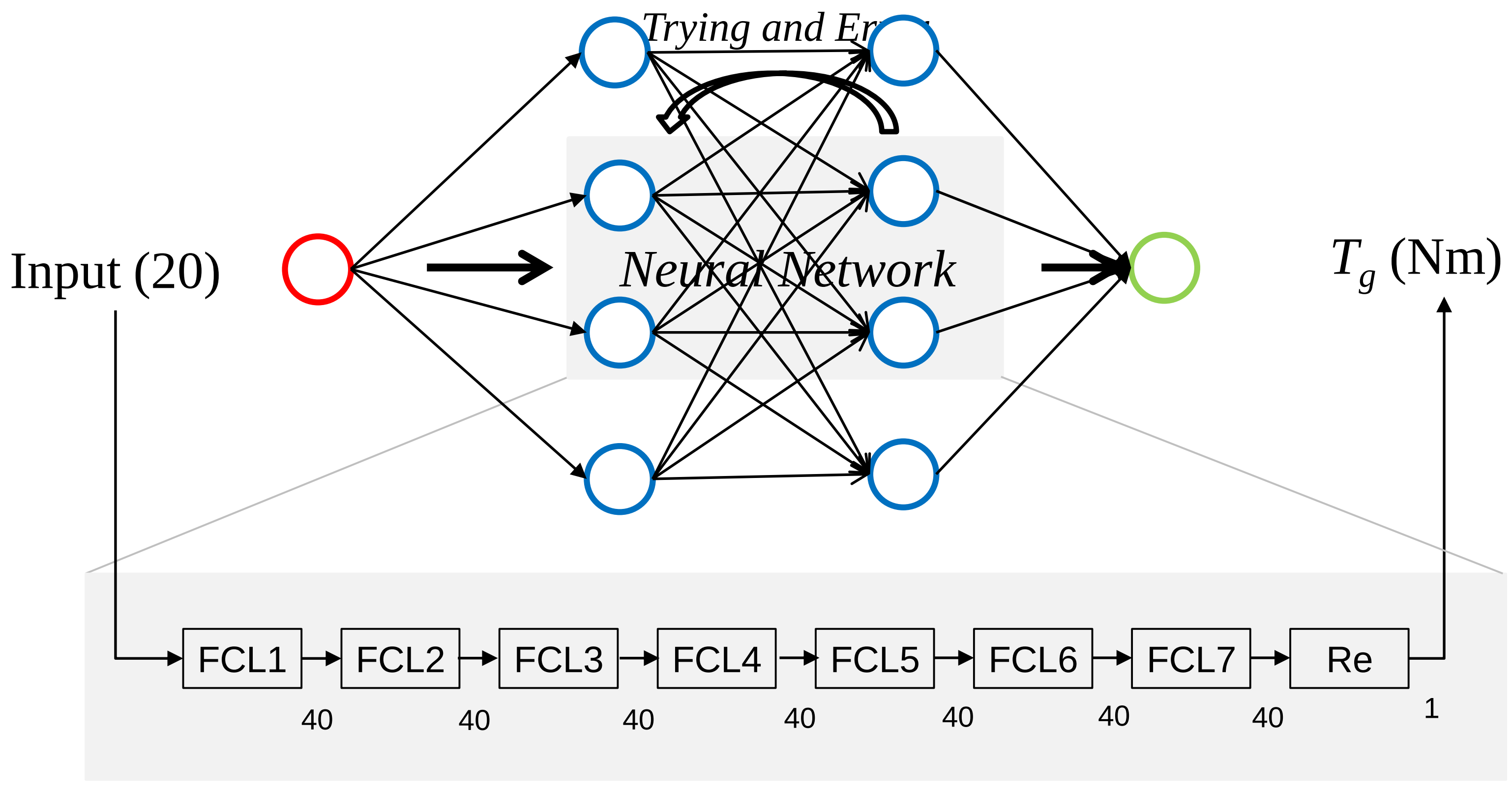
Supervised Learning:
Regression Model w.r.t. Engine Switching

- T_e/T_g prediction model with FCL structure w.r.t. engine switching

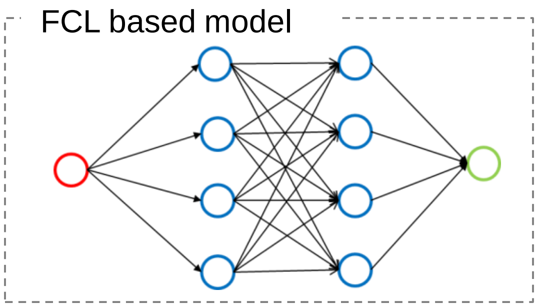


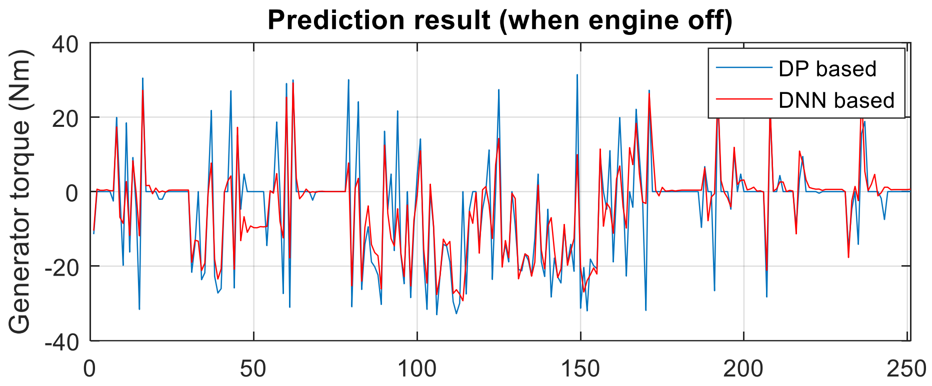
Supervised Learning:
Regression Model when Engine Off

- T_g prediction model with fully-connected layer



Supervised Learning:
Prediction Result for FCL Model when Engine Off

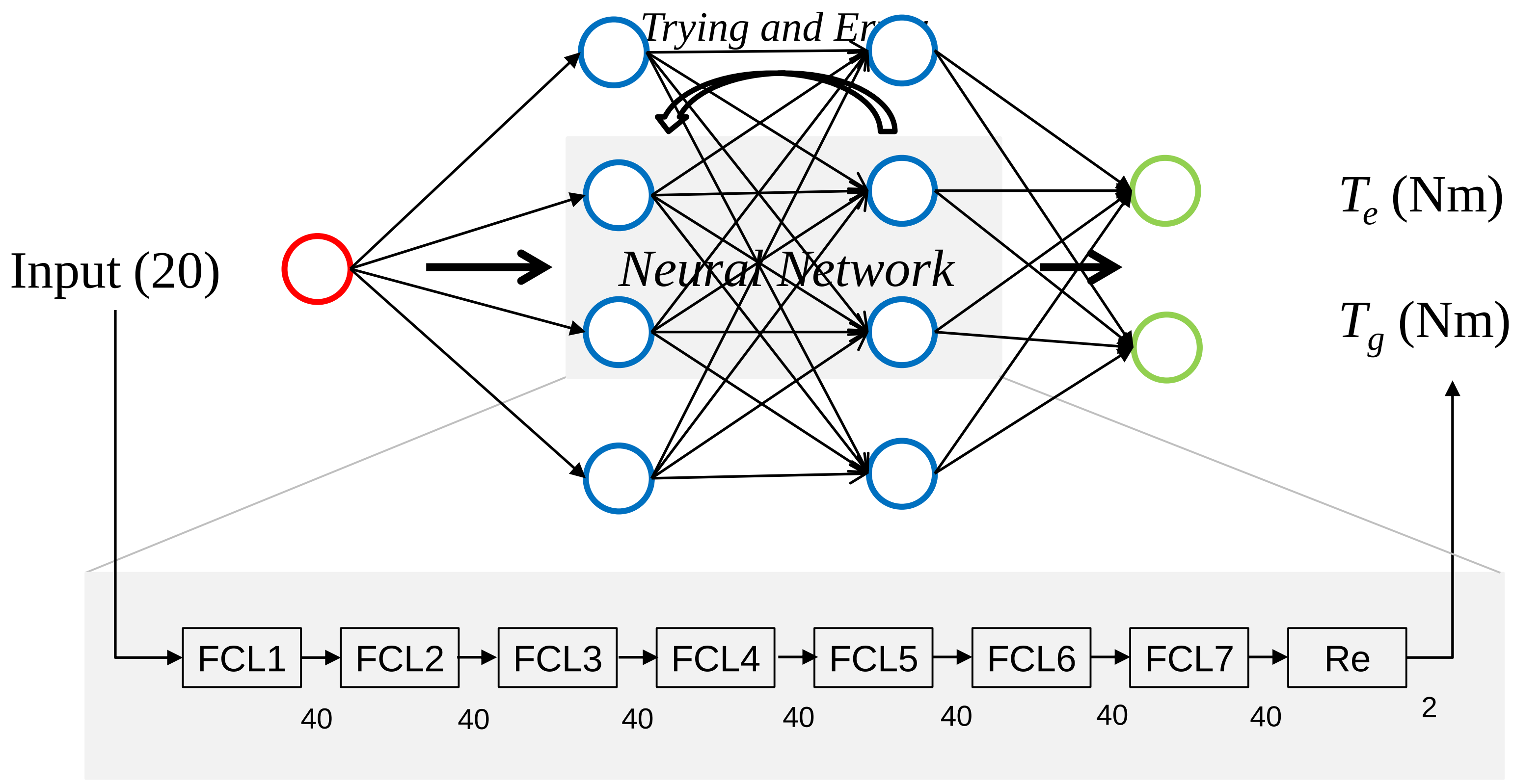




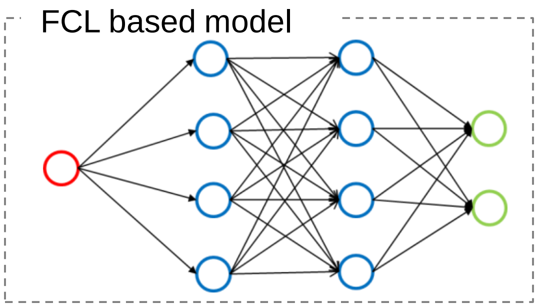
RMSE	Train result	Test result (US06)
Tg	3.1208	7.0292

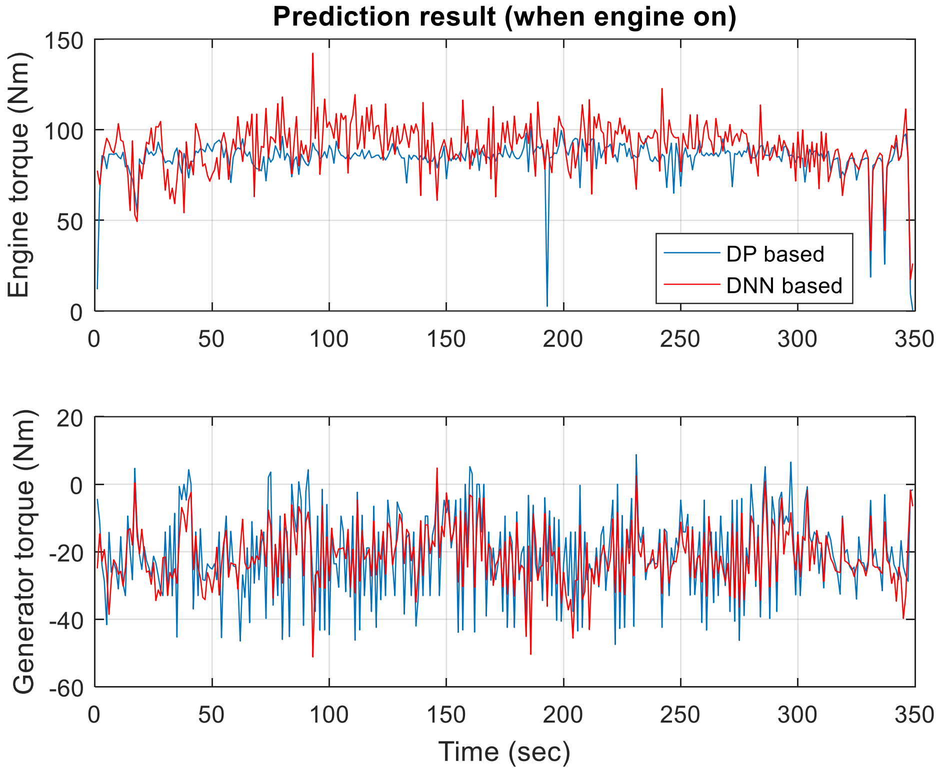
Supervised Learning:
Regression Model when Engine On

- T_e/T_g prediction model with fully-connected layer



Supervised Learning:
Prediction Result for FCL Model when Engine On

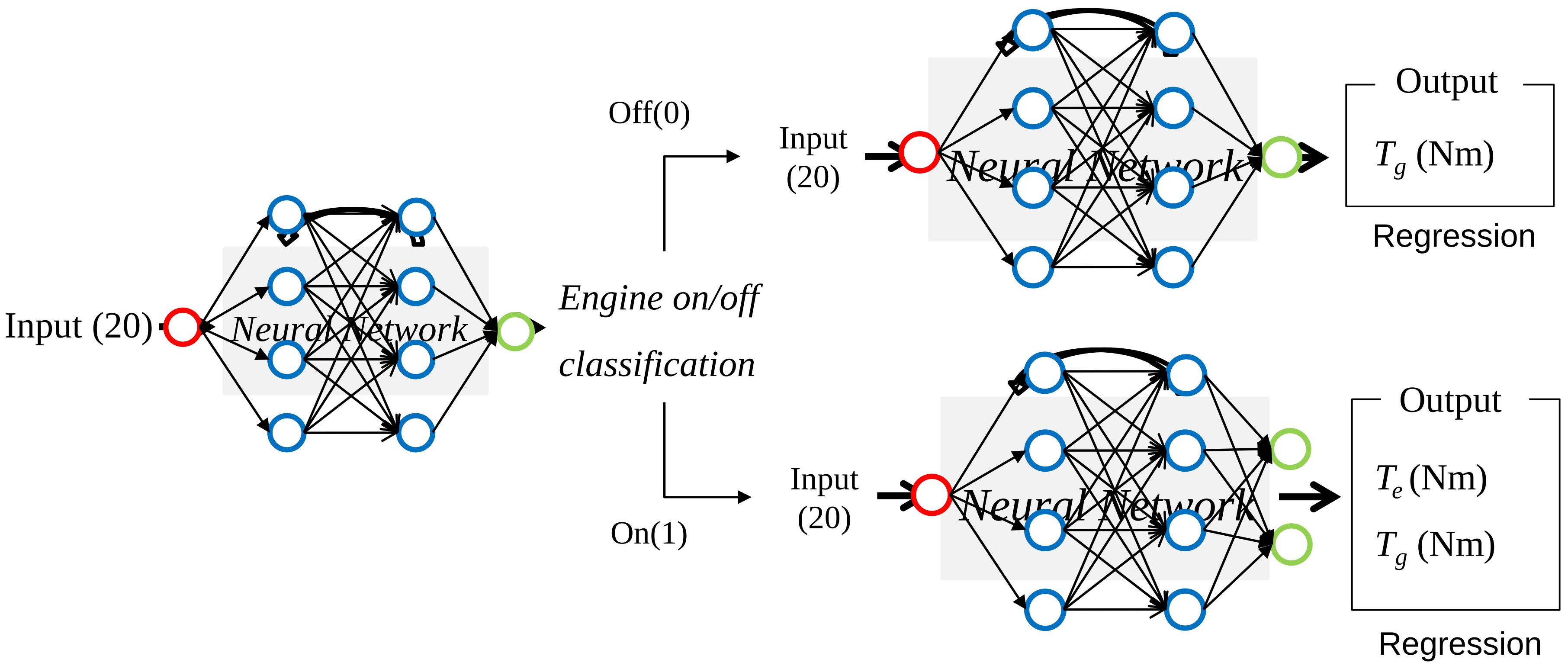




RMSE	Train result	Test result (US06)
T_e	8.4417	14.5458
T_g	3.1392	8.3587

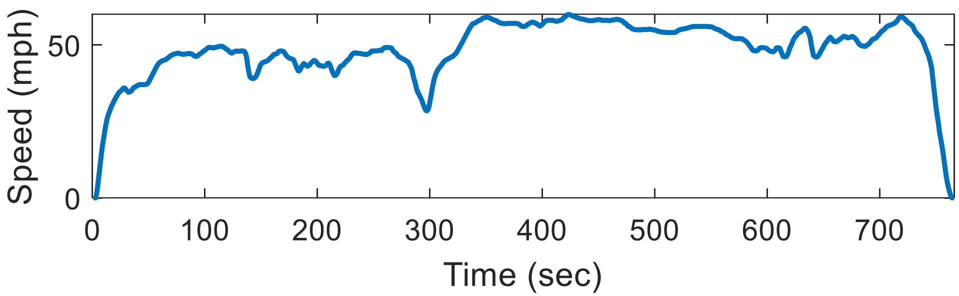
Supervised Learning:
Final Model for PMS Control

- Engine switching prediction with FCL structure → T_e/T_g prediction with FCL structure



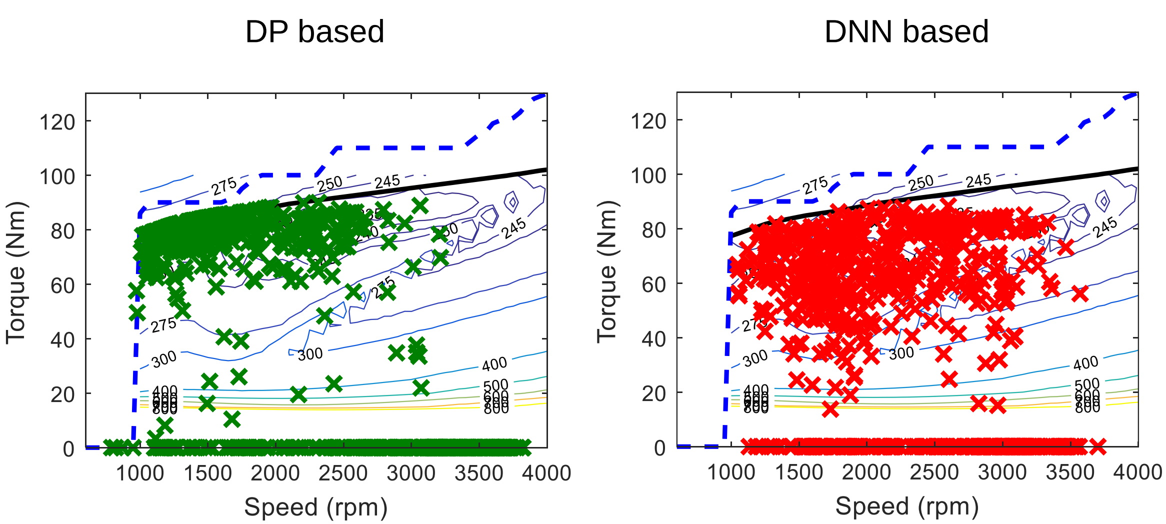
Supervised Learning:
Simulation Validation for Final Model

- Validation with train data (one of a highway cycle)

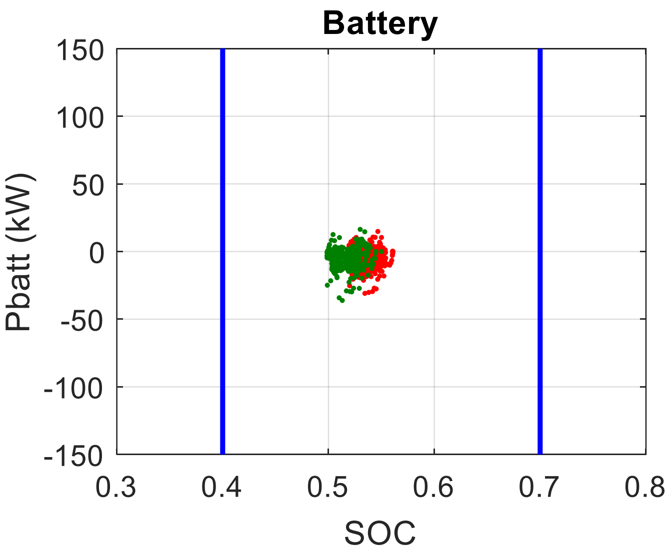


	Fuel Efficiency [mpg]
DP based	55.0117
DNN based	49.8925 (90.69%)

엔진 작동 구간

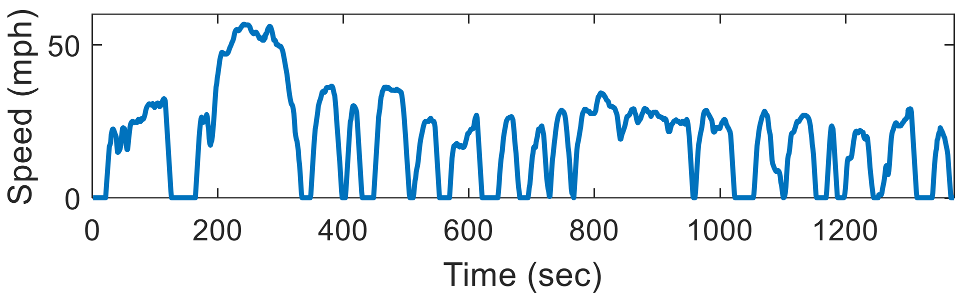


배터리 작동 구간



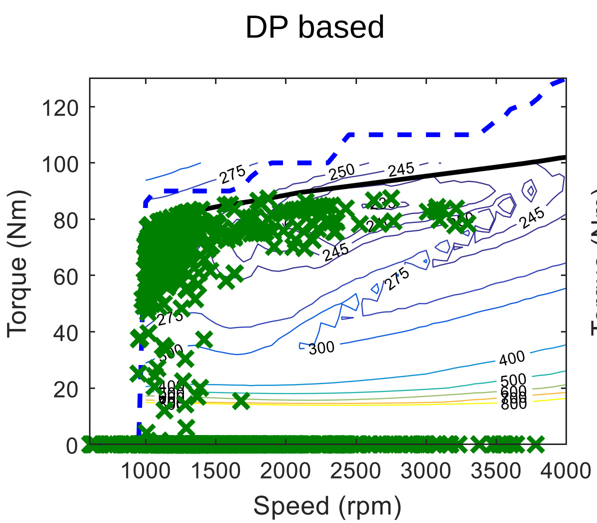
Supervised Learning:
Simulation Validation for Final Model

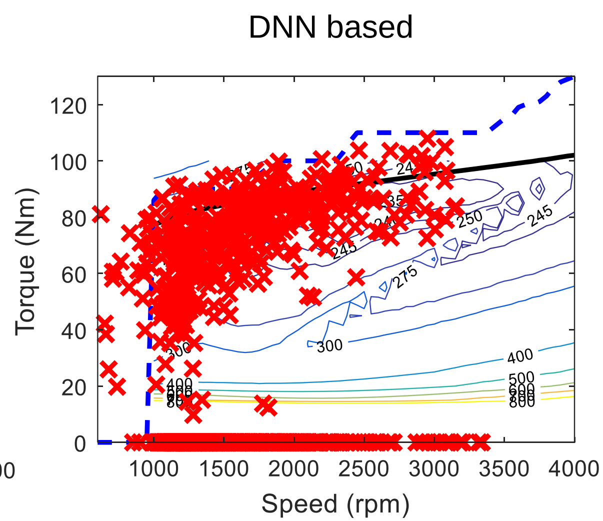
- Validation with train data (one of a city cycle)



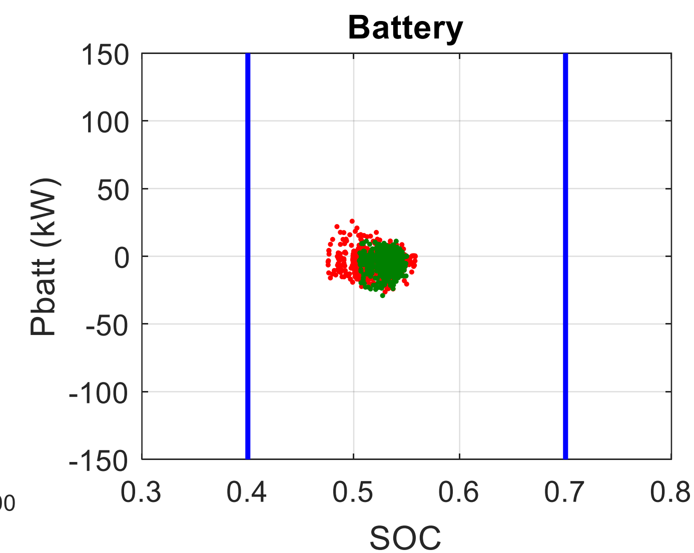
	Fuel Efficiency [mpg]
DP based	57.8730
DNN based	34.4497 (78.20%)

엔진 작동 구간



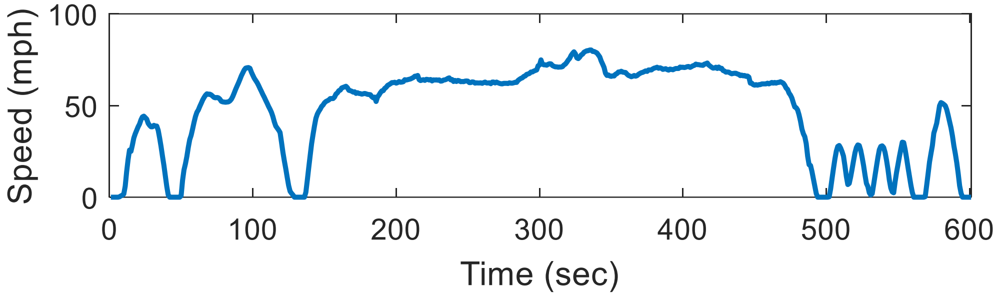


배터리 작동 구간



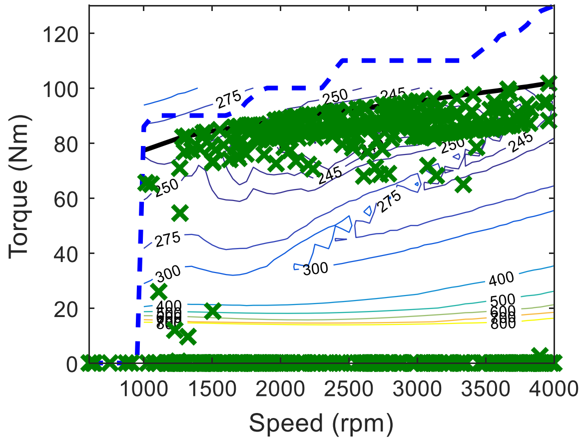
Supervised Learning:
Simulation Validation for Final Model

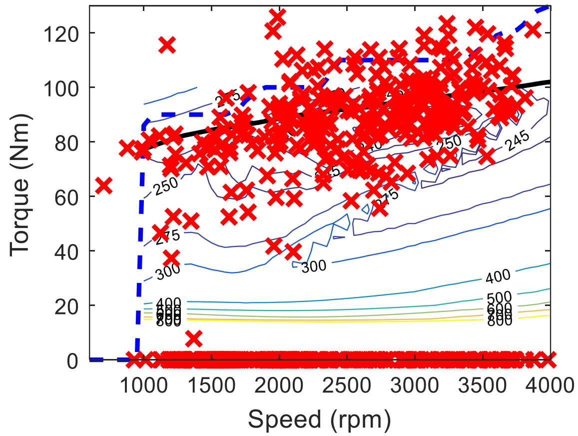
- Validation with test data



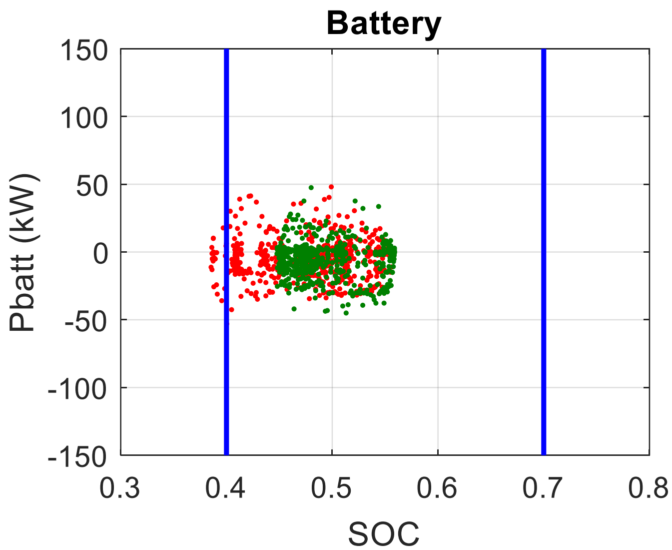
	Fuel Efficiency [mpg]
DP based	38.6082
DNN based	36.1688 (93.68%)

엔진 작동 구간





배터리 작동 구간

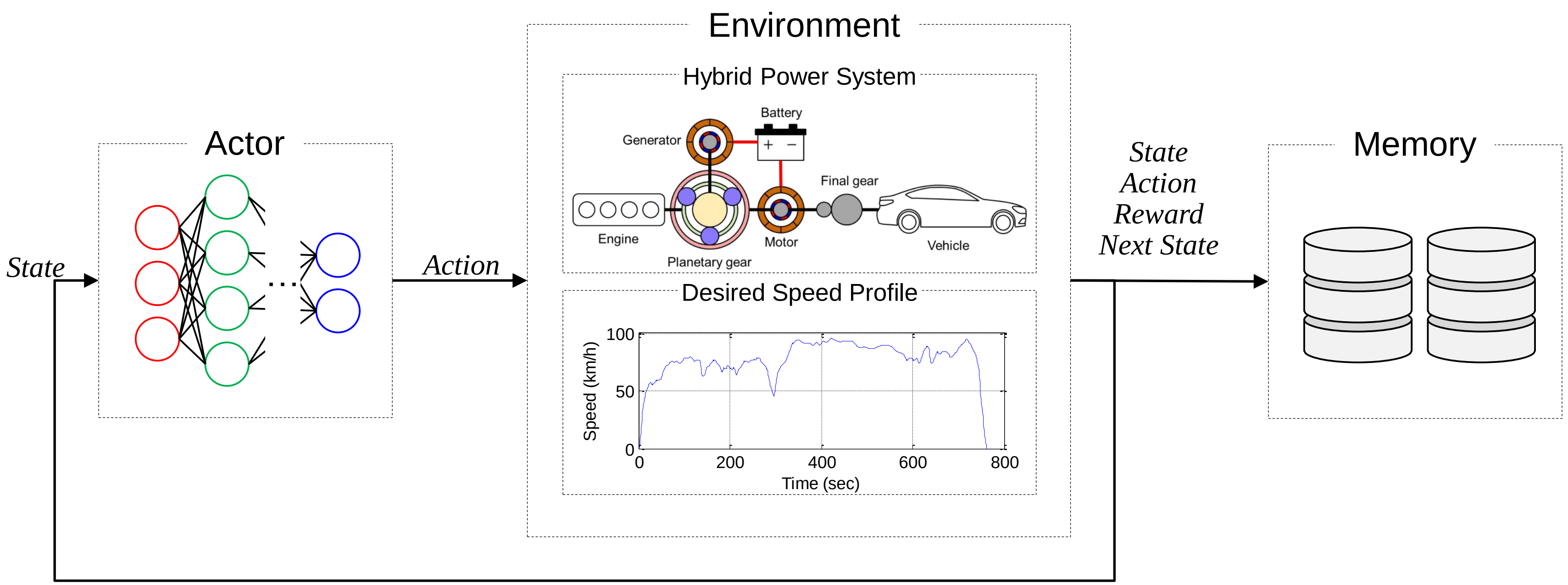


Reinforcement Learning

Reinforcement Learning:
Deep Deterministic Policy Gradients

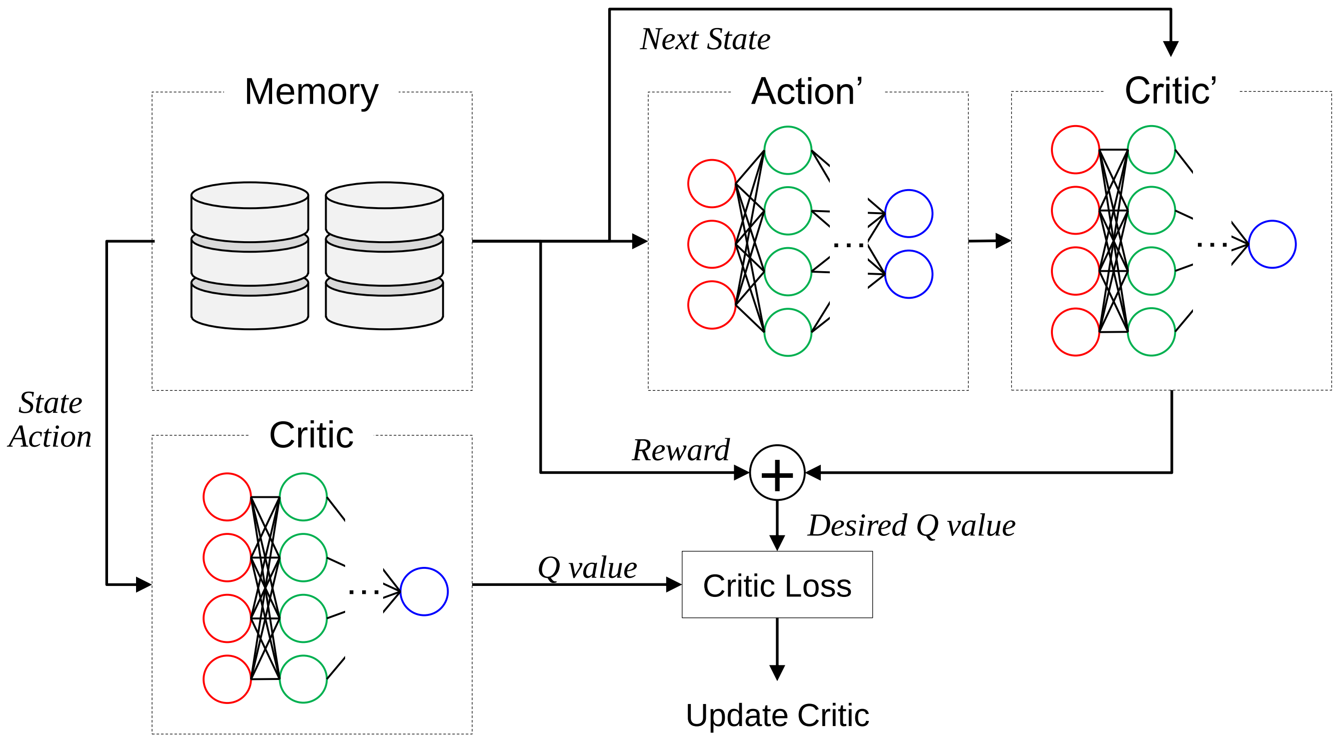
The model trained by the loop with 2 steps
1) Exploration
2) Optimization

- 1) Exploration



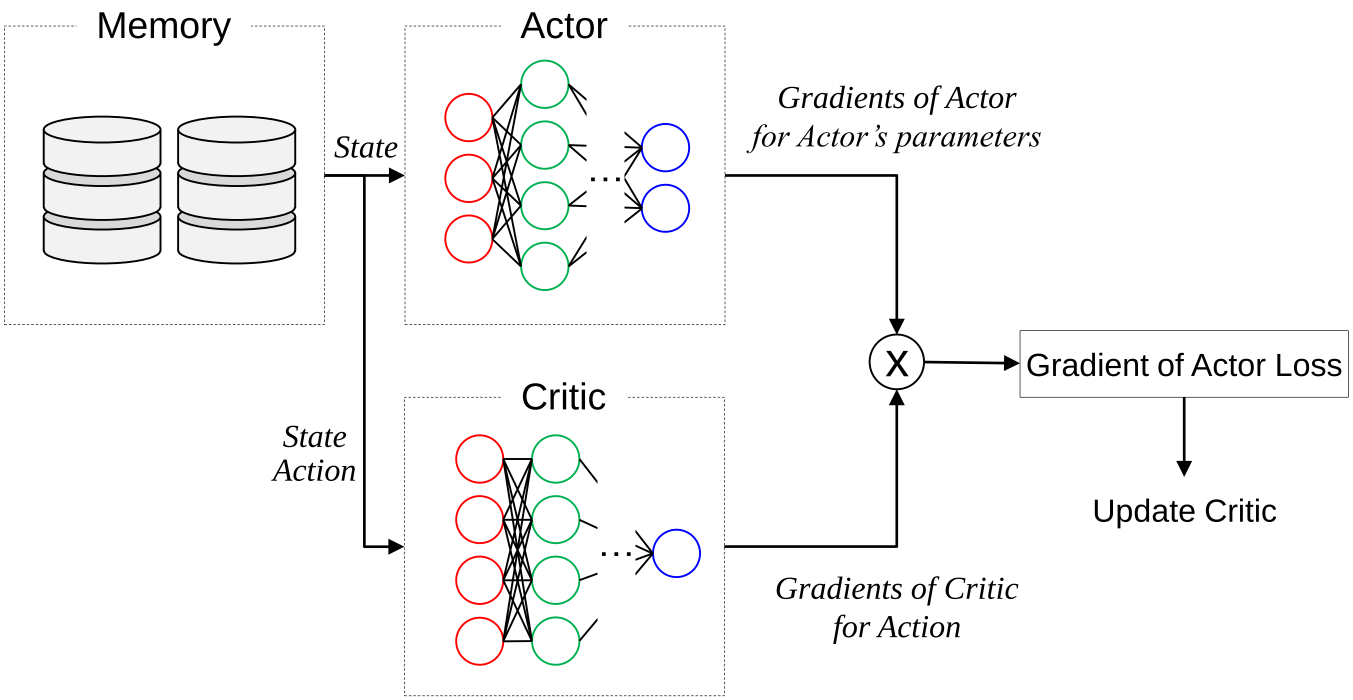
Reinforcement Learning:
Deep Deterministic Policy Gradients

- 2) Optimization – Update Critic



Reinforcement Learning:
Deep Deterministic Policy Gradients

- 2) Optimization – Update Actor

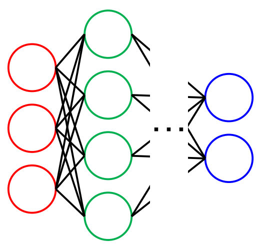


- 3) Soft copy Actor' and Critic'

Lillicrap, Timothy P., et al. "Continuous control with deep reinforcement learning." *arXiv preprint arXiv:1509.02971* (2015).

Reinforcement Learning:
Structure of Actor and Critic

Actor

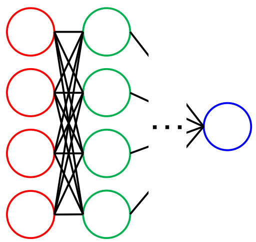


Inputs: acceleration, generator speed, engine speed, motor speed, SOC, mean of velocity, std of velocity (5)

Outputs: desired engine torque, desired engine speed (2)

Hidden layers: 5 hidden layers with 30 nodes (leaky relu)

Critic



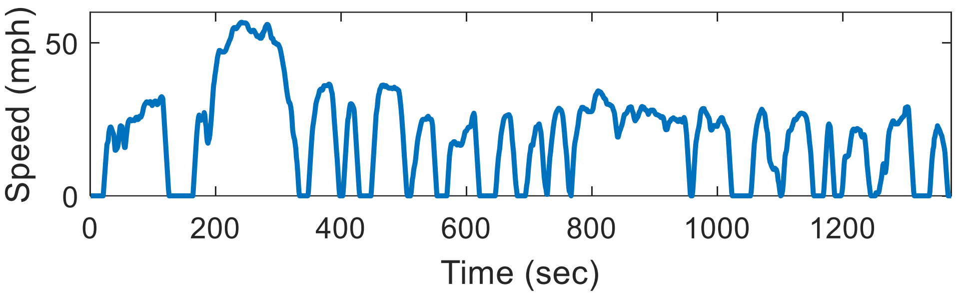
Inputs: acceleration, generator speed, engine speed, motor speed, SOC, desired engine torque, desired engine speed, mean of velocity, std of velocity (9)

Outputs: Q value (1)

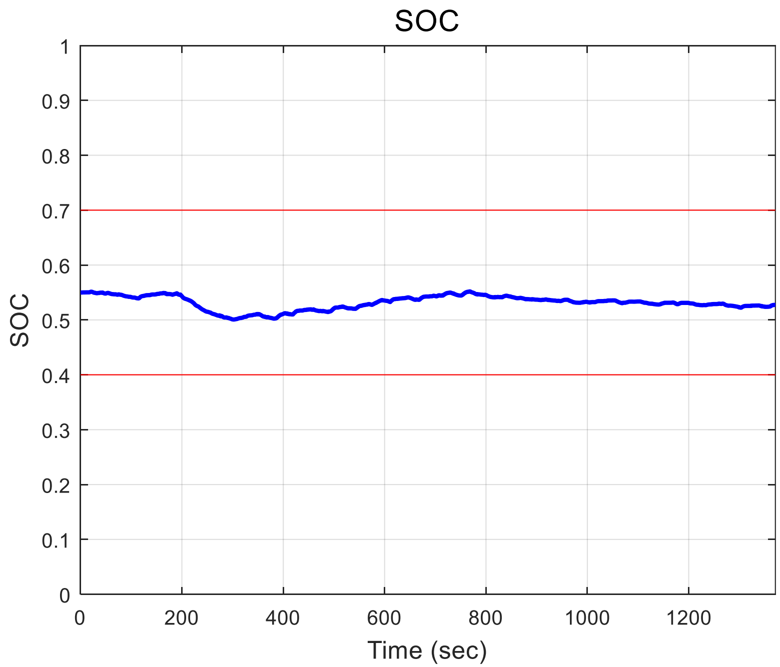
Hidden layers: 5 hidden layers with 40 nodes (leaky relu)

Reinforcement Learning:
Result

- One of a city cycle



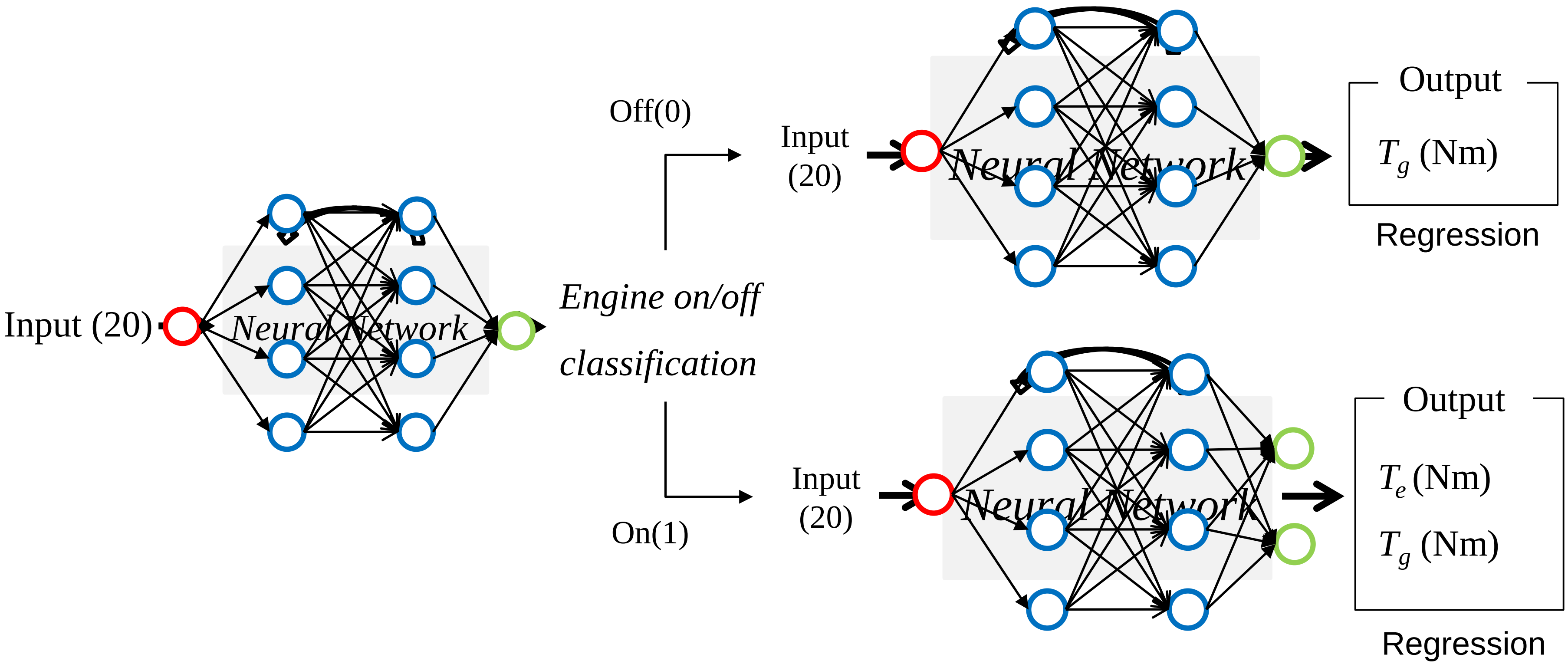
	Fuel Efficiency [mpg]
DP based	57.8730
RL based	29.9903 (51.82%)



Conclusions

Conclusions

- PMS control with supervised learning



DNN based fuel efficiency	36.1688 mpg (93.68%)

Conclusions

- PMS control with reinforcement learning

The fuel consumption performance is worse than DNN

➔ The states can not represent the features clearly

- Similar inputs with different outputs → Not trainable dataset)

➔ The inputs with exploration are loosely bounded

- Without precise bound, explorations are useless (ex: break the SOC bound or cycle)

	Fuel Efficiency [mpg]
DP based	57.8730
RL based	29.9903 (51.82%)

Thank you