Supplementary Materials for Physics-Informed Deep Learning: A Hybrid Paradigm for Traffic State Estimation Informed By Second-Order Traffic Models

Rongye Shi¹, Zhaobin Mo¹, Xuan Di^{1,2}

¹School of Engineering and Applied Science, Columbia University, New York, NY, USA ²Data Science Institute, Columbia University, New York, NY, USA rongyes@alumni.cmu.edu, zm2302@columbia.edu, sharon.di@columbia.edu

The LWR-PIDL TSE method using the three-parameter LWR model is described as follows:

$$\rho_{t} + (Q(\rho))_{x} = 0,$$

$$Q(\rho) = \sigma \left(a + (b - a) \frac{\rho}{\rho_{max}} - \sqrt{1 + y^{2}} \right),$$

$$u = Q(\rho)/\rho,$$

$$a = \sqrt{1 + (\delta p)^{2}},$$

$$b = \sqrt{1 + (\delta (1 - p))^{2}},$$

$$y = \delta \left(\frac{\rho}{\rho_{max}} - p \right),$$
(1)

where δ , p and σ are the three free parameters as the function is named. The parameters σ and p control the maximum flow rate and critical density (where the flow is maximized), respectively. δ controls the roundness level of $Q(\rho)$. In addition to the above-mentioned three parameters, the maximum density ρ_{max} is also part of the model parameters. Thus, the model parameters are $\lambda = (\delta, p, \sigma, \rho_{max})$. The residual is redesigned as follows:

$$\hat{f}(t, x; \theta, \lambda) := \hat{\rho}_t(t, x; \theta)
+ (Q(\hat{\rho}(t, x; \theta); \delta, p, \sigma, \rho_{max}))_x,$$
(2)

The PIDL structure for this baseline method is given in Fig.1. In this structure, the PUNN estimates the density $\hat{\rho}$ directly, but the averaged velocity \hat{u} is inferred from the model, which is part of the PINN.

The learning loss is

$$Loss_{\theta, \lambda} = MSE_o + MSE_a$$

$$\begin{split} = & \frac{1}{N_o} \sum_{i=1}^{N_o} \alpha_1 |\hat{\rho}(t_o^{(i)}, x_o^{(i)}; \theta) - \rho^{(i)}|^2 + \alpha_2 |\hat{u}(t_o^{(i)}, x_o^{(i)}; \theta) - u^{(i)}|^2 \\ & + \frac{1}{N_a} \sum_{j=1}^{N_a} \beta |\hat{f}(t_a^{(j)}, x_a^{(j)}; \theta, \lambda)|^2, \end{split} \tag{3}$$

where both \hat{u} and \hat{f} are calculated by PINN, and only $\hat{\rho}$ is from PUNN.

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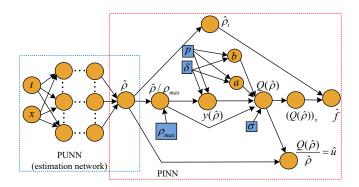


Figure 1: The structure of LWR-PIDL.