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DISCRIMINATOR-BASED INNER LAYER FORCING MODEL FOR WALL BOUNDED FLOWS OVER ROUGH WALLS

Ming Liu
Center for Research on Innovative Simulation Software
Institute of Industrial Science
The University of Tokyo
4-6-1 Komaba, Meguro-ku, Tokyo, Japan
liuming@iis.u-tokyo.ac.jp

Simon Dalpke
Institute of Fluid Mechanics
Karlsruhe Institute of Technology
76131 Karlsruhe, Germany
simon.dalpke@kit.edu

Alexander Stroh
Institute of Fluid Mechanics
Karlsruhe Institute of Technology
76131 Karlsruhe, Germany
alexander.stroh@kit.edu

Yosuke Hasegawa
Center for Research on Innovative Simulation Software
Institute of Industrial Science
The University of Tokyo
4-6-1 Komaba, Meguro-ku, Tokyo, Japan
ysk@iis.u-tokyo.ac.jp

ABSTRACT

Simulations of turbulent flows over rough walls are usually linked to prohibitively high computational cost, hence various simplified models are often used to consider the effects of roughness on the turbulent flow field. However, the model performance strongly depends on the proper selection of parameters linked to the roughness geometry. We present an inner layer forcing model based on training a discriminator that can distinguish between well-resolved flow fields over rough walls and under-resolved ones over smooth walls. The discriminator is integrated as an inner layer forcing model by introducing a body force term to Navier-Stokes equation. The under-resolved flow fields on a coarse grid are dynamically modified to mimic the well-resolved fields over rough walls. The discriminator-based inner layer forcing models are applied to three rough surface topographies ($k/\delta = 1/12$, $1/11.2$, and $1/6.7$) at three Reynolds numbers, i.e., $Re_\tau = 180$, 360, and 500. The predicted mean velocity and root mean squared (rms) profiles on coarse grids show good agreement with roughness-resolved simulations. The relative error of U_b^+ is less than 4% for low roughness cases at a moderate Reynolds number.

INTRODUCTION

Turbulent flows over rough walls exist in various engineering applications. The rough surfaces are commonly associated with a dramatic increase in skin friction drag, leading to a higher energy consumption. A characterization of roughness effects on turbulent flow can be performed in costly experiments or using Direct Numerical Simulations (DNSs). The computational cost for such roughness-resolved DNS is extremely high due to a broad spectrum of turbulent flow and roughness scales. To reduce costs, the effects of roughness on the outer flow are often modeled without resolving small-scale structures in the near-wall region.

Most existing models are devised to establish a correlation between equivalent sand roughness height k_s and various statistical geometrical parameters of a particular rough surface (Forooghi *et al.* (2017)). Then, the roughness function ΔU^+, representing the shift of the mean velocity profile in the logarithmic layer, can be predicted accordingly. One common method for roughness modelling is to introduce a body force layer close to the wall to represent roughness effects, also called parametric forcing approach. However, a set of forcing parameters have to be calibrated for each considered rough surface, so general representation of roughness remains challenging (Busse & Sandham (2012)).

Machine learning introduces another powerful tool to develop such models. For instance, it improves predictions for a wide range of rough surfaces based on statistics of roughness topography reducing the prediction error below 10% (Yang *et al.* (2023)). However, the selection of appropriate inputs from a variety of geometric parameters is a prerequisite for these models. Recently, a discriminator-based inner layer forcing model (Liu *et al.* (2025)) is developed by dynamically modify an under-resolved flow fields to mimic well-resolved ones on a coarse grid. It shows accurate predictive performance for turbulent flows over smooth surface, and is further extended in the present contribution for rough walls.

DATASET GENERATION

An incompressible fully developed turbulent channel flow over rough walls under a constant pressure gradient is considered in the present study. A computational domain in the size of $L_x \times L_y \times L_z$ is utilized, where x, y, and z are streamwise, wall-normal and spanwise directions. For simulations over rough walls, L_y is set as $2(\delta + k_{md})$, where δ is the half channel height defined from the mean height of the rough walls, and k_{md} is mean (meltdown) roughness height. The rough surface is symmetrically applied on the top and bottom of the channel. Also, the turbulent channel flows over smooth walls are considered as reference cases, and the corresponding domain size in the wall-normal direction is fixed at 2δ. A no-slip boundary condition is set at upper and lower walls, and periodic boundary conditions are adopted in the streamwise and spanwise directions.

Totally three friction Reynolds numbers, i.e., $Re_\tau = u_\tau\delta/\nu = 180, 360$, and 500, are considered in the present study, where u_τ and ν are the friction velocity and the kinematic viscosity. As shown in Fig. 1, we consider three types of rough walls with mean peak-to-trough heights of $k = \delta/12$, $\delta/11.2$, and $\delta/6.7$. The first roughness is a surface scan of a grit-blasted surface (Thakkar *et al.*, 2018) whereas the other two are artificially generated based on a prescribed power spectrum and probability density function following the procedure outlined in Yang *et al.* (2023). The surfaces are tiled from the original smaller samples to fill the channel dimensions (see Fig. 1). Table 1 summarizes the computational setups for DNSs of turbulent flows over rough and smooth surfaces on fine and coarse grids, respectively.

The DNSs of turbulent flows over the rough walls are performed using the GPU accelerated finite difference solver `CaNS` (Costa (2018)). In `CaNS` the roughness is represented by a volume-penalization immersed boundary method on a cartesian grid, where a grid refinement is present towards the walls. The numerical tool has been successfully validated for rough surfaces against literature data. For the statistical analysis temporal and spatial averaging is applied based on instantaneous snapshots taken from the fully-developed simulation state omitting the initial transient phase. The DNSs of turbulent flows over the smooth walls are also performed on a coarse grid using `OpenFOAM` (version 8). It is known that the coarse DNSs over the smooth wall can overestimate U_b^+ compared to the corresponding fine DNS over the smooth wall due to the absence of small-scale structures (Liu *et al.* (2025)). As shown in Table 1, the U_b^+ obtained by the fine DNS over the rough wall under the same Re_τ is even lower due to the effect of the roughness.

INNER LAYER FORCING MODEL

The entire framework to develop a discriminator-based inner layer forcing model for rough walls is illustrated in Fig. 2. Firstly, DNSs of well-resolved flow fields over rough walls and under-resolved flow fields over smooth walls are performed to construct training datasets. Then, a deep neural network representing the discriminator is trained to discriminate instantaneous flow fields obtained from the two simulations with different grid resolutions. Finally, the well-trained discriminator is integrated as an inner layer forcing model to correct an instantaneous flow fields obtained by the under-resolved simulations.

Discriminator

Instantaneous velocity fields at specific wall parallel location $y^+ = y_m^+$ are extracted from well-resolved and under-resolved DNS results. Then, the well-resolved velocity fields on a fine grid are filtered onto the corresponding coarse grid. These filtered well-resolved and under-resolved instantaneous velocity fields on the wall parallel plane with three components in the size of $N_x \times N_z \times 3$ are then further normalized by subtracting its mean value and dividing it by its standard deviation. The results serve as input to the discriminator. In this way, only the fluctuating information at specific wall parallel location is provided to the discriminator. The label of 0 for the true data from the fine DNS and 1 for unauthentic data from the coarse DNS is adopted as the output. The discriminator consists of 3 convolutional-pooling blocks and 2 dense layers. The ReLU activation functions are used for the hidden layers, while the sigmoid function is applied at the output layer. The Adam algorithm is employed as the optimizer with binary cross-entropy as the loss function.

Inner layer forcing model

The discriminator is integrated as an inner layer forcing model by introducing a body forcing term f_i into the momentum transport equation as,

$$\frac{\partial u_i}{\partial t} + u_j\frac{\partial u_i}{\partial x_j} = -\frac{\partial p}{\partial x_i} + \frac{1}{Re_\tau}\frac{\partial^2 u_i}{\partial x_j \partial x_j} + f_i. \tag{1}$$

The body forcing f_i is calculated by

$$f_i = \eta\left(u_i^{\mathrm{upd}} - u_i^{\mathrm{ini}}\right)\delta\left(y^+ - y_m^+\right), \tag{2}$$

where η is an amplification coefficient. The updated velocity u_i^{upd} is determined through an iterative algorithm according to the derivative of the output of the discriminator with respect to the normalized flow fields by,

$$u_i^{n+1} = u_i^n - \alpha\,\frac{\partial\mathscr{D}(\theta, u_i^n)}{\partial u_i^n} \tag{3}$$

where n, $\mathscr{D}$, θ, α denote the update iteration, the discriminator prediction value and the update step size, respectively. This velocity update is conducted iteratively until the discriminator output is smaller than a given criterion, chosen to be 0.1. The body forcing term drives the instantaneous velocities to approach well-resolved ones at the forcing location $y^+ = y_m^+$, and resultant flow fields become indistinguishable from well-resolved results.

The above methodology is implemented using the machine learning library `PyTorch`. After the discriminator is trained, `LibTorch`, a `C++` distribution of `PyTorch`, is employed to implement the well-trained discriminator into a `OpenFOAM` solver, i.e., `pimpleFoam`, so as to determine the inner layer forcing.

RESULTS

Training of discriminator

For each rough case, the discriminator is trained using well-resolved results over the rough wall and the corresponding under-resolved results over the smooth wall in the same computational domain. The instantaneous flow fields at the same wall-normal location from the lower and upper walls are adopted as the training and the test datasets, respectively. Figure 3 plots the discriminator output of training and test datasets for the case of the rough wall $k/\delta = 1/11.2$ under $Re_\tau = 180$ at the wall-normal location $y^+ = 20$. It is validated that a discriminator can be trained to discriminate well-resolved flow fields over rough walls and under-resolved flow fields with good accuracy. This well-trained discriminator will be adopted to determine the inner-layer forcing in the following subsections.

Prediction of bulk mean velocity

Then, the DNSs on coarse grids with the discriminator-based inner layer forcing models are performed by implementing it into `OpenFOAM` simulations. For each rough topography, three different wall parallel locations are considered, i.e.,

y^+ = 10, 20 and 30 for Re_τ = 180, and y^+ = 10, 20 and 50 for Re_τ = 360 and 500. The wall-parallel location y^+ = 50 that is further away from the wall is considered under higher Re_τ cases as to avoid the interference between the forcing location and the rough surface due to the reduction of the wall unit dimension. Figure 4 summarizes the predicted bulk mean Reynolds number $Re_b = 2U_b\delta/\nu$ under a constant Re_τ by the coarse DNSs with the present inner layer forcing model. After introducing the present inner layer forcing model, the simulation results on the coarse grids approach to the corresponding fine DNS results over the rough walls, especially under a moderate Reynolds number and a moderate roughness. It is worth noting that, the relative error of predicted U_b^+ compared to the roughness-resolved DNS reference resulting in less than 4% for the cases k/δ = 1/12 and 1/11.2 under Re_τ = 180.

Influence of forcing location

Under Re_τ = 180, the results obtained by the coarse DNS with the present forcing model using the forcing location y^+ = 20 and 30 exhibit better accuracies than that using the forcing location y^+ = 10. This suggests that the forcing location around the buffer layer is effective in correcting the under-resolved flow fields, and it is consistent with our previous study on the inner-layer forcing model for wall turbulence over smooth walls.

However, as Re_τ increases, the prediction using the forcing location $y^+ = 20$ also deteriorates, while the results obtained by that using the forcing locations y^+ = 50 show a more accurate prediction. Our previous studies (Liu *et al.* (2025)) on DNSs with the present forcing model show that the the forcing location y^+ = 20 is still effective as Re_τ increases up to 1000 for turbulent flows over smooth walls. However, the simulations results for rough walls suggest that the forcing location further away from the wall is a better choice under a higher Re_τ. The performance degradation for the forcing location around the buffer layer, i.e., y^+ = 20, is attributed to the interference between the forcing location and the rough wall under a high Re_τ. In the roughness-resolved simulations, the presence of a rough wall on the wall-parallel plane corresponding to the forcing location results in a constant zero-velocity region. However, in the present inner-layer forcing model, since only the fluctuation information is considered on the forcing location, the zero-velocity region within the rough wall cannot be properly reproduced, thus affecting the predictive performance of the forcing model.

Predicted mean and rms velocity profiles

The predicted mean and rms velocity profiles along the wall-normal direction under Re_τ = 180 obtained by the simulations with the inner layer forcing model at the forcing location at y^+ = 20 are plotted in Fig. 5 for three rough walls. The corresponding results obtained by the fine DNS over rough walls and the coarse DNSs over smooth walls are also plotted for comparison. As shown in Fig. 5, the mean velocity profiles obtained by the coarse DNS approach the well-resolved results after introducing the inner layer forcing. Although the forcing is only imposed at a single location in the inner layer, the mean velocity profile in the outer layer can be reproduced accurately, resulting in a satisfactory prediction of the bulk mean velocity U_b^+. The inner layer forcing model also improves the prediction of rms velocity profiles. In the coarse DNS without a inner forcing model, the streamwise rms velocity is overestimated, while spanwise and wall-normal rms velocities are underestimated. By comparison, all the rms velocity profiles approach to the corresponding results obatined by the fine DNS after the inner layer forcing model is adopted.

CONCLUSIONS & OUTLOOK

A deep-neural-network-based discriminator is trained to distinguish well-resolved flow fields over rough walls from under-resolved ones over smooth walls. Then, a discriminator-based inner layer forcing model is developed by introducing a body forcing term. It dynamically forces the under-resolved instantaneous velocities to approach well-resolved results. The inner layer forcing models are adopted to three rough surfaces (k/δ = 1/12, 1/11.2,and 1/6.7) at three Reynolds numbers, i.e., Re_τ = 180, 360, and 500. The predicted mean and rms velocity profiles on coarse grids show good agreement with roughness-resolved results. The relative error of U_b^+ is less than 4% for the cases k/δ = 1/12 and 1/11.2 under Re_τ = 180 with the forcing location $y^+ = 20$. The prediction gradually deteriorates as Re_τ increases, while a forcing location that is further away from the wall can improve predictions under high Re_τ cases. The prediction using the present forcing model also become worse for the rough wall with high roughness, i.e., k/δ = 1/6.7, due to the larger peak height and resultant complex flow patterns. In summary, the present discriminator-based inner layer forcing model works well for low roughness cases at a moderate Reynolds number.

In the future, the physical mechanism on how the present forcing model represent rough wall features and improve simulation results will be investigated more thoroughly to improve the understanding of the working principle.

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Table 1: Computational details for DNSs of channel flow over rough and smooth walls. Here, N_x, N_y, and N_z denote the number of grid points in three directions. Δx and Δz are the grid size in the streamwise and spanwise directions, and Δy_{min} and Δy_{max} are the minimum and the maximum grid size in the wall-normal direction. U_b^+ is the bulk mean velocity in wall units.

k/δ	$L_x/\delta \times (L_y - 2k_{md})/\delta \times L_z/\delta$	Re_τ	$N_x \times N_y \times N_z$	$\Delta x, \Delta y_{min}, \Delta y_{max}, \Delta z$	U_b^+
1/12	5.63×2×2.815	180	384×257×192	2.64, 0.45, 4.20, 2.63	13.79
1/12	5.63×2×2.815	360	460×380×230	4.40. 0.61, 5.68. 4.40	13.52
1/12	5.63×2×2.815	500	690×600×345	4.08. 0.54, 4.99. 4.08	13.25
1/11.2	6×2×3	180	384×257×192	2.81, 0.56, 2.91. 2.81	14.73
1/11.2	6×2×3	360	460×340×230	4.70, 0.84, 4.40, 4.70	15.55
1/11.2	6×2×3	500	690×500×345	4.35, 0.53, 4.33, 4.35	15.78
1/6.7	6×2×3	180	384×257×192	2.81, 0.54, 2.83. 2.81	8.90
1/6.7	6×2×3	360	460×340×230	4.70, 0.81, 4.26. 4.70	8.61
1/6.7	6×2×3	500	690×500×345	4.35, 0.51, 4.19. 4.35	8.65
0	5.63×2×2.815	180	30×18×30	33.78, 2.45, 61.20, 16.89	20.89
0	5.63×2×2.815	360	60×36×60	33.78, 2.57, 64.23, 16.89	24.31
0	5.63×2×2.815	500	90×54×90	31.28, 2.41, 60.36, 15.64	24.69
0	6×2×3	180	32×18×32	33.75, 2.45, 61.20, 16.88	20.89
0	6×2×3	360	32×18×32	33.75, 2.45, 61.20, 16.88	24.31
0	6×2×3	500	32×18×32	33.75, 2.45, 61.20, 16.88	24.69

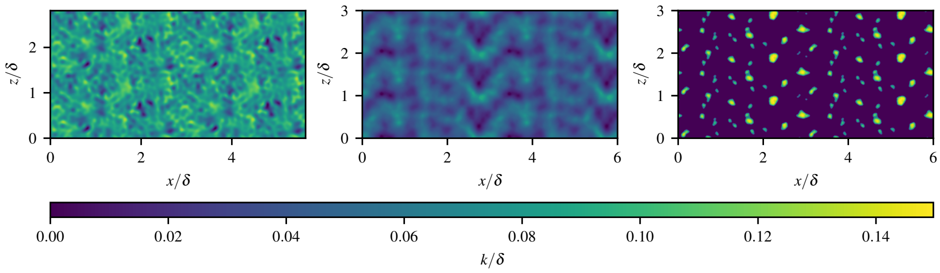

Figure 1: Roughness topography for rough walls k/δ = 1/12, 1/11.2, and 1/6.7 (from left to right).

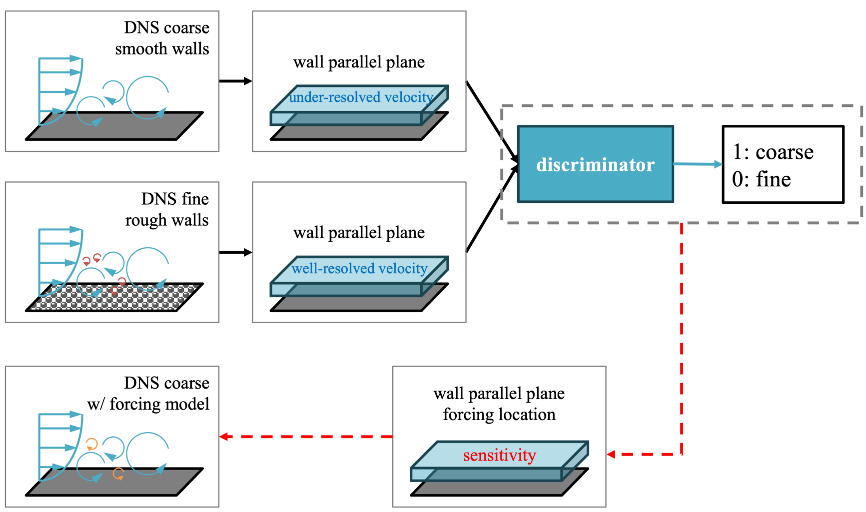

Figure 2: Schematic of discriminator-based inner layer forcing models.

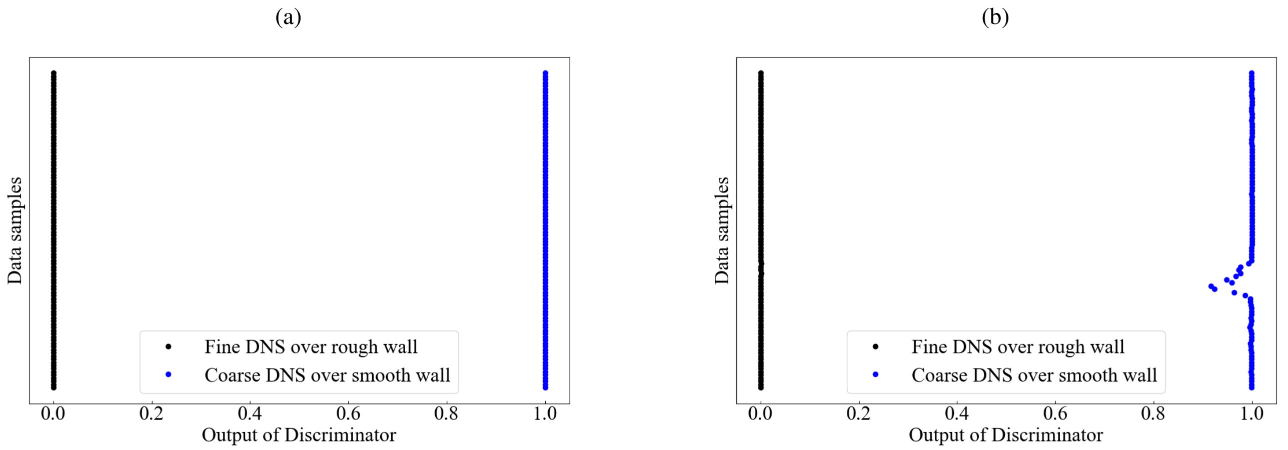

Figure 3: Discriminator output of (a) training and (b) test datasets. The case of the rough wall $k/\delta = 1/11.2$ under $Re_\tau = 180$ at the wall-normal location $y^+ = 20$ is plotted as an example.

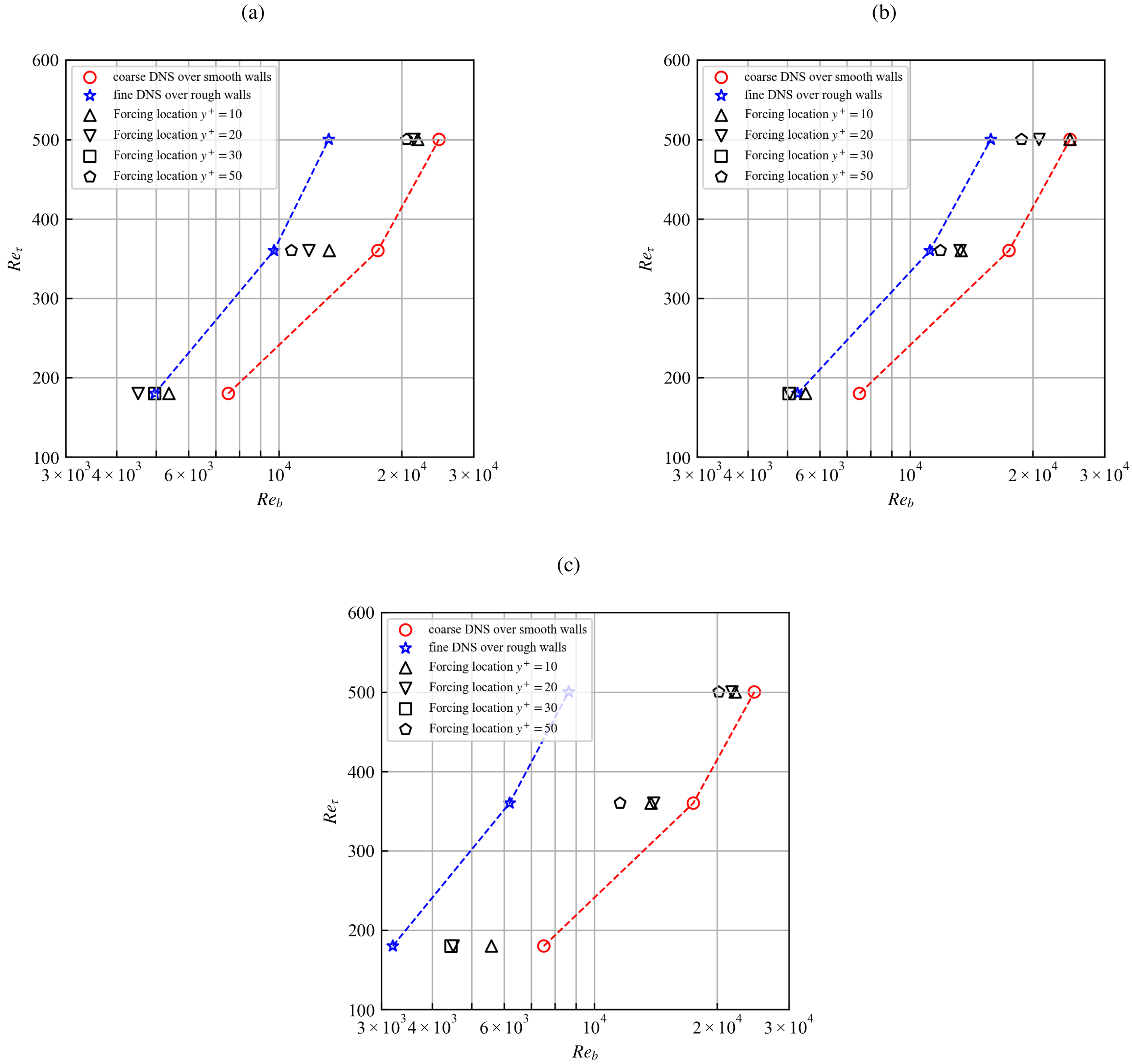

Figure 4: Summary of predicted Re_b under a constant Re_τ by the coarse DNSs with the present inner layer forcing model for rough walls k/δ = (a) 1/12, (b) 1/11.2, and (c) 1/6.7.

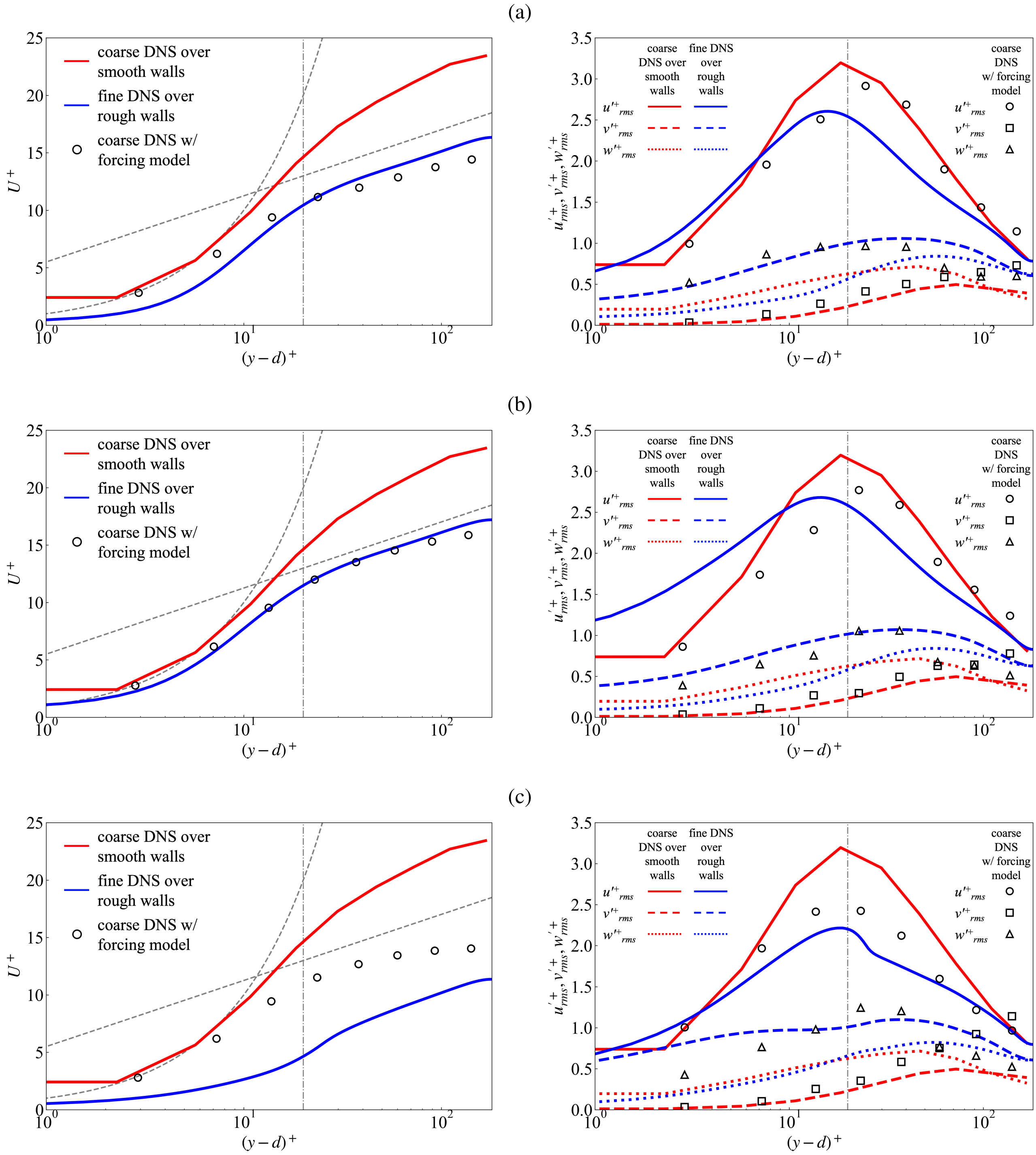

Figure 5: Mean (left) and rms (right) velocity profiles of simulations with discriminator-based inner layer forcing models using the forcing location $y^+ = 20$ for rough walls k/δ = (a) 1/12, (b) 1/11.2, and (c) 1/6.7 under $Re_\tau = 180$. The vertical dashed dotted lines indicate the forcing location, and d refers to zero plane displacement.