

A Physics-Informed, PIV-Based Method for Surface Pressure Reconstruction

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ABSTRACT

A physics-informed method is proposed for reconstructing surface pressure from PIV data. The method formulates the reconstruction as a weighted least-squares optimization problem in which the surface pressure is represented by B-spline basis functions and constrained by local and global physical conditions. The standard deviation of the surface-normal pressure gradient, evaluated from the PIV-based pressure field, is introduced as a physically meaningful indicator of local uncertainty and is used to define the weighting function in the optimization. The same quantity is also used to locate the suction peak directly from the PIV data. A global constraint, derived from the Navier–Stokes equation over a control volume surrounding the body, is introduced to anchor the reconstructed pressure distribution outside the suction region. The method is assessed using time-averaged 3D-LPT data for a NACA 0015 airfoil at $\alpha = 10^\circ$ and $Re_c = 2 \times 10^5$. The reconstructed surface pressure shows very good agreement with pressure-tap measurements. In the leading-edge region, where direct extrapolation is most sensitive to velocity and pressure-gradient errors, the reconstruction error is reduced by approximately a factor of three.

1. Introduction

Surface pressure provides a direct link between the flow field and the resulting aerodynamic or hydrodynamic loads, moments, and energy transfer. Accurate knowledge of surface pressure is therefore essential for validating numerical simulations, interpreting separation and unsteady-flow mechanisms, and developing reliable design and control strategies for fluid–structure interaction systems. Conventional surface-pressure measurements are commonly obtained using pressure taps or pressure-sensitive paint (PSP) (Gregory et al., 2008). Pressure taps provide direct and accurate point measurements, but they are intrusive, have limited spatial resolution, and are difficult to implement on small, thin, or geometrically complex three-dimensional bodies. PSP provides spatially resolved pressure information, but it requires careful calibration and illumination control, is sensitive to temperature effects, and can be limited in temporal response.

PIV-based pressure reconstruction offers a non-intrusive alternative by estimating pressure from measured velocity fields through the momentum equation (Van Oudheusden, 2013). This approach provides spatially and, when time-resolved data are available, temporally resolved pressure fields, making it particularly attractive for complex or unsteady aerodynamic and hydrodynamic flows. Recent developments in large-scale tomographic PIV (Scarano, 2012) and three-dimensional Lagrangian particle tracking (3D-LPT) (Schröder & Schanz, 2023) have further extended pressure-from-PIV methods from canonical laboratory configurations towards more realistic flow problems.

Despite this progress, accurate reconstruction of surface pressure from PIV data remains a challenging task (Ragni et al., 2009; Tagliabue et al., 2017; Jux et al., 2020; Cakir et al., 2024). PIV provides velocity information in the flow domain, whereas the pressure at the solid boundary is not measured directly and must be inferred by integration, extrapolation, or optimization. The resulting surface pressure is sensitive to measurement noise, spatial resolution, near-wall data availability, pressure boundary conditions, and the treatment of high-gradient regions. These difficulties are particularly important near stagnation points, suction peaks, and separated-flow regions, where the pressure field changes rapidly and where the aerodynamic loads are strongly affected. Standard extrapolation methods can provide acceptable results over large portions of the surface, but they often lose accuracy in precisely those regions where the pressure information is most physically relevant.

The present work introduces a physics-informed method for PIV-based surface pressure reconstruction. The method combines a weighted least-squares formulation with local and global physical constraints. The central idea is to use the statistical behaviour of the pressure gradient along surface-normal lines as an indicator of the reliability of near-wall pressure extrapolation. Specifically, the standard deviation of the surface-normal pressure gradient is used to construct a spatially varying weighting function in the optimization. Regions where the normal pressure gradient varies strongly are treated as locally uncertain, so the reconstruction is allowed to deviate from the direct extrapolation while remaining smooth and physically constrained. The same statistical indicator is also used to detect key aerodynamic features, such as the suction peak, directly from the PIV-based pressure field.

The paper is organized as follows. Section 2 presents the reconstruction method, including the cost function, weighting strategy, and physical constraints. Section 3 applies the method to a NACA 0015 airfoil case and compares the reconstructed pressure with pressure-tap data. Section 4 summarizes the main findings and implications of the proposed approach.

2. Surface Pressure Reconstruction Method

Direct evaluation of surface pressure from PIV-based pressure fields is commonly performed using linear (Ragni et al., 2009) or higher-order (Tagliabue et al., 2017) extrapolation from the near-wall flow region to the solid boundary. These methods can be accurate over surface regions where the pressure varies smoothly in the wall-normal direction. However, even when the boundary layer is thin, significant errors may occur near suction peaks and stagnation points because the pressure gradient changes rapidly as the wall is approached. These regions are also among the most important for aerodynamic-load prediction. Therefore, instead of accepting the extrapolated pressure as the final result, the present method uses it as an initial physically based estimate and embeds it in an optimization framework.

The reconstruction strategy is illustrated in Fig. 1 for a NACA 0015 airfoil at an angle of attack of 10° . The surface is parameterized by the normalized curvilinear coordinate $\hat{s}$, and the pressure information reconstructed from PIV in the near-wall region is sampled along surface-normal lines. The objective is to determine a smooth and physically consistent surface-pressure distribution that remains close to the reliable parts of the extrapolated pressure while being corrected in regions where extrapolation is uncertain.

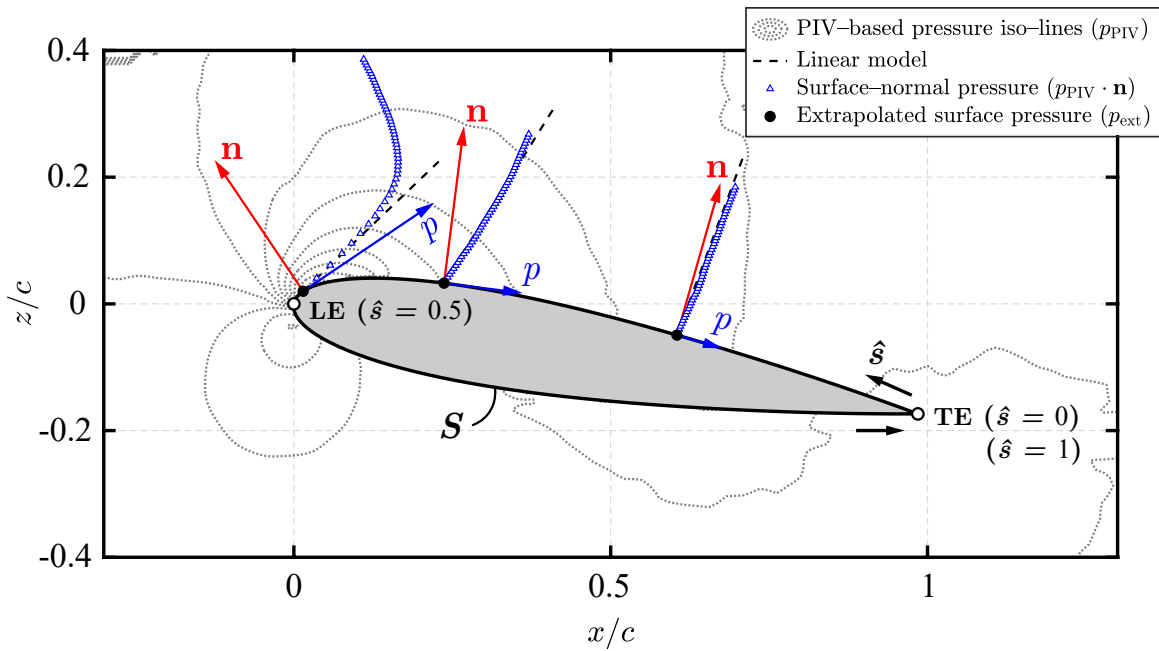


Figure 1. Schematic of the airfoil model and the main quantities used in the surface-pressure reconstruction method. The PIV-based pressure field is sampled along surface-normal lines and used to estimate both the extrapolated surface pressure and the local uncertainty indicator.

2.1. Cost-function formulation

Let $p_S(\tilde{s})$ denote the surface pressure distribution along the airfoil surface S , parameterized by the normalized curvilinear coordinate $\tilde{s}$ (Fig. 1). The coordinate starts at the trailing edge and follows the airfoil contour; for a symmetric airfoil such as the NACA 0015, the leading edge is located at approximately $\tilde{s} = 0.5$. The surface pressure is reconstructed by minimizing the following cost function:

$$J = \sum_{i=1}^{N_s} w_i [p_S(\tilde{s}_i) - p_{\text{ext}}(\tilde{s}_i)]^2 + \lambda \int_S \left(\frac{\partial^2 p_S}{\partial \tilde{s}^2} \right)^2 d\tilde{s}. \quad (1)$$

The first term enforces agreement between the reconstructed pressure and the pressure obtained by near-wall extrapolation. The second term penalizes non-physical oscillations and promotes a smooth pressure distribution along the surface. The surface pressure is represented by B-spline basis functions (Piegl & Tiller, 1995),

$$p_S(\tilde{s}) = \sum_{k=1}^M c_k B_k(\tilde{s}), \quad (2)$$

where $B_k(\tilde{s})$ are the B-spline basis functions, c_k are the corresponding control coefficients, and M is the number of basis functions. This representation provides an inherently smooth pressure curve and allows derivatives of p_S to be evaluated analytically. The number of basis functions must be sufficiently large to capture physical pressure features such as suction peaks, but not so large that the solution becomes sensitive to noise.

The extrapolated pressure $p_{\text{ext}}(\tilde{s}_i)$ is obtained from the PIV-based pressure field. First, the pressure field is reconstructed from the measured velocity data using the incompressible Navier–Stokes equation,

$$\nabla p = -\rho \frac{D\mathbf{u}}{Dt} + \mu \nabla^2 \mathbf{u}, \quad (3)$$

where ρ and μ are the fluid density and dynamic viscosity, respectively. Further details on pressure reconstruction from PIV are given by Van Oudheusden (2013). In the present work, the iterative domain partitioning (IDP) method (Donțu et al., 2026) is used to reduce pressure-integration error propagation and sensitivity to boundary conditions. At each surface location $\tilde{s}_i$, pressure samples are then taken along the local outward normal direction $\mathbf{n}$ and linearly extrapolated to the wall to obtain $p_{\text{ext}}(\tilde{s}_i)$. This extrapolated pressure provides a useful local estimate, but it is not imposed as the final solution because it may contain large errors near strong pressure gradients.

The coefficient w_i in Eq. 1 is a spatially varying weight that controls the local confidence in $p_{\text{ext}}(\tilde{s}_i)$. Large values of w_i force the optimized pressure to remain close to the extrapolated pressure,

whereas small values allow the optimization to rely more strongly on smoothness and physical constraints. In the present method, w_i is determined from the standard deviation of the surface-normal pressure gradient, as described in the next subsection. The regularization parameter λ controls the global balance between data fidelity and smoothness. In this study, λ is taken as a constant. For flows containing discontinuities or very sharp physical gradients, such as shock waves, λ could also be made spatially dependent to avoid over-smoothing of genuine flow features.

2.2. Surface-normal pressure gradient

The main uncertainty in near-wall extrapolation arises when the pressure varies strongly along the surface-normal direction. As shown in Fig. 1, this is commonly observed near suction peaks and stagnation regions, where a linear extrapolation model cannot accurately represent the near-wall pressure variation. To quantify this behaviour, the surface-normal pressure gradient is evaluated along each normal line. For a point located at a distance n from the wall along the normal direction $\mathbf{n}$, the normal pressure gradient is defined as

$$g(n; \tilde{s}_i) = \nabla p_{\text{PIV}}(\mathbf{x}_S(\tilde{s}_i) + n\mathbf{n}) \cdot \mathbf{n}, \quad (4)$$

where $\mathbf{x}_S(\tilde{s}_i)$ is the surface point corresponding to $\tilde{s}_i$. The standard deviation of this quantity along the normal line is then computed as

$$\sigma_n(\tilde{s}_i) = \left[\frac{1}{N_n - 1} \sum_{j=1}^{N_n} (g(n_j; \tilde{s}_i) - \bar{g}(\tilde{s}_i))^2 \right]^{1/2}, \quad (5)$$

with

$$\bar{g}(\tilde{s}_i) = \frac{1}{N_n} \sum_{j=1}^{N_n} g(n_j; \tilde{s}_i), \quad (6)$$

where N_n is the number of pressure-gradient samples along the normal line. A large value of σ_n indicates strong variation of the normal pressure gradient and, consequently, a higher probability that direct extrapolation to the wall is unreliable.

The weighting function in Eq. 1 is defined as

$$w_i = \frac{1}{\sigma_n(\tilde{s}_i) + \epsilon}, \quad (7)$$

where ϵ is a small positive constant introduced to avoid division by zero. With this definition, surface locations with smooth and stable normal pressure-gradient behaviour receive a larger weight,

whereas high-gradient regions receive a smaller weight and are corrected by the optimization. In addition to defining the weights, σ_n can be used as an objective indicator of aerodynamic features. Peaks in σ_n often coincide with surface-pressure extrema and therefore provide a data-driven way to locate suction peaks and other high-gradient regions directly from the PIV-based pressure field.

2.3. Optimization constraints

The optimization is supplemented by physical constraints to improve the uniqueness and consistency of the reconstructed surface pressure. Local constraints can be imposed at special locations. For example, at a stagnation point the pressure coefficient is expected to approach unity, while near the leading edge the reconstructed pressure must remain smooth and physically bounded. These constraints help stabilize the solution in regions where the extrapolated pressure is uncertain.

A global constraint is also introduced to connect the reconstructed surface pressure to the pressure and velocity fields in the surrounding flow. The constraint is obtained from the Navier–Stokes equation integrated over a control volume CV that encloses the body surface S . Denoting the outer boundary of the control volume by CS , the following relation can be written:

$$\iint_S \nabla p_S \cdot \mathbf{n} \, d\tilde{s} = - \iint_S \left[\nabla \left(\frac{1}{2} \rho |\mathbf{u}_S|^2 \right) + \rho (\boldsymbol{\omega}_S \times \mathbf{u}_S) \right] \cdot \mathbf{n} \, ds - \iint_{CS} [\nabla(p+q) + \rho(\boldsymbol{\omega} \times \mathbf{u})] \cdot \mathbf{n} \, ds. \quad (8)$$

Here, $\mathbf{u}_S$ and $\boldsymbol{\omega}_S$ are the translational and angular velocity vectors of the solid surface, respectively, p is the static pressure, and $q = \rho |\mathbf{u}|^2 / 2$ is the dynamic pressure. For a fixed solid body, the surface-velocity contribution vanishes. In the present steady airfoil case, evaluation of the right-hand side over the control-volume boundary shows that the net contribution is close to zero. Therefore, the following simplified constraint is used in the optimization:

$$\iint_S \nabla p_S \cdot \mathbf{n} \, d\tilde{s} = 0. \quad (9)$$

This condition provides a global balance that prevents the reconstructed pressure from being biased towards the extrapolated pressure in regions where local information alone is insufficient.

3. Results and Discussion

The proposed method is applied to a time-averaged PIV dataset obtained for a NACA 0015 airfoil at an angle of attack of 10° and a chord-based Reynolds number of $Re_c = 2 \times 10^5$. The measurements were performed using 3D-LPT in the open-jet wind-tunnel facility at Delft University of

Technology. The airfoil model was bounded at both ends, and the flow in the measurement volume was approximately two-dimensional. Therefore, the volumetric velocity data were averaged in the spanwise direction to obtain a high-quality two-dimensional velocity field. The pressure field was reconstructed from Eq. 3 using the IDP method. Further details on the experimental setup, measurement procedure, and pressure reconstruction are available in Donđu et al. (2026).

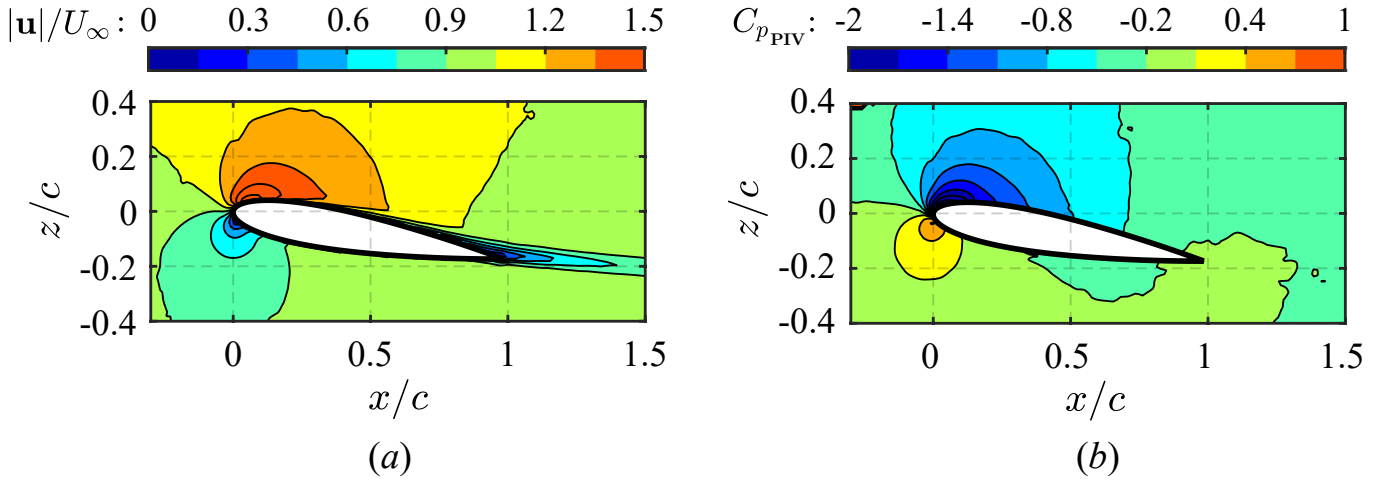


Figure 2. Representative time- and span-averaged fields obtained from the PIV/LPT data: (a) non-dimensional velocity magnitude and (b) reconstructed pressure coefficient.

Figure 2 shows the non-dimensional velocity magnitude and the corresponding pressure-coefficient field reconstructed from the PIV data. These fields provide the input for the surface-pressure reconstruction method discussed in the following subsections.

3.1. Surface-normal pressure-gradient behaviour

Figure 3(a) compares the surface pressure coefficient obtained by linear extrapolation with the pressure-tap measurements. The comparison shows that the linear extrapolation captures the general pressure distribution but produces significant errors near the leading edge. In particular, both the suction-peak magnitude and its location are not accurately recovered. Figure 3(b) presents the standard deviation of the surface-normal pressure-gradient distribution, σ_n . The highest values of σ_n occur near the leading edge, where the extrapolation error is also largest. This confirms that σ_n provides a physically meaningful indicator of local uncertainty in the extrapolated pressure.

The maximum of σ_n occurs close to the suction-peak location measured by the pressure taps. To estimate this position more accurately, a two-term Gaussian function is fitted to the σ_n distribution. The maximum of the fitted function identifies the suction-peak location with an error of approximately 1.5%, whereas the suction-peak location obtained from direct linear extrapolation has an error of approximately 3.5%. Since the present dataset is of high quality and does not suffer

from strong wall reflections, the difference is expected to become even more important in more challenging experimental conditions. These results demonstrate that σ_n is useful not only as an optimization weight, but also as an objective detector of the suction-peak location.

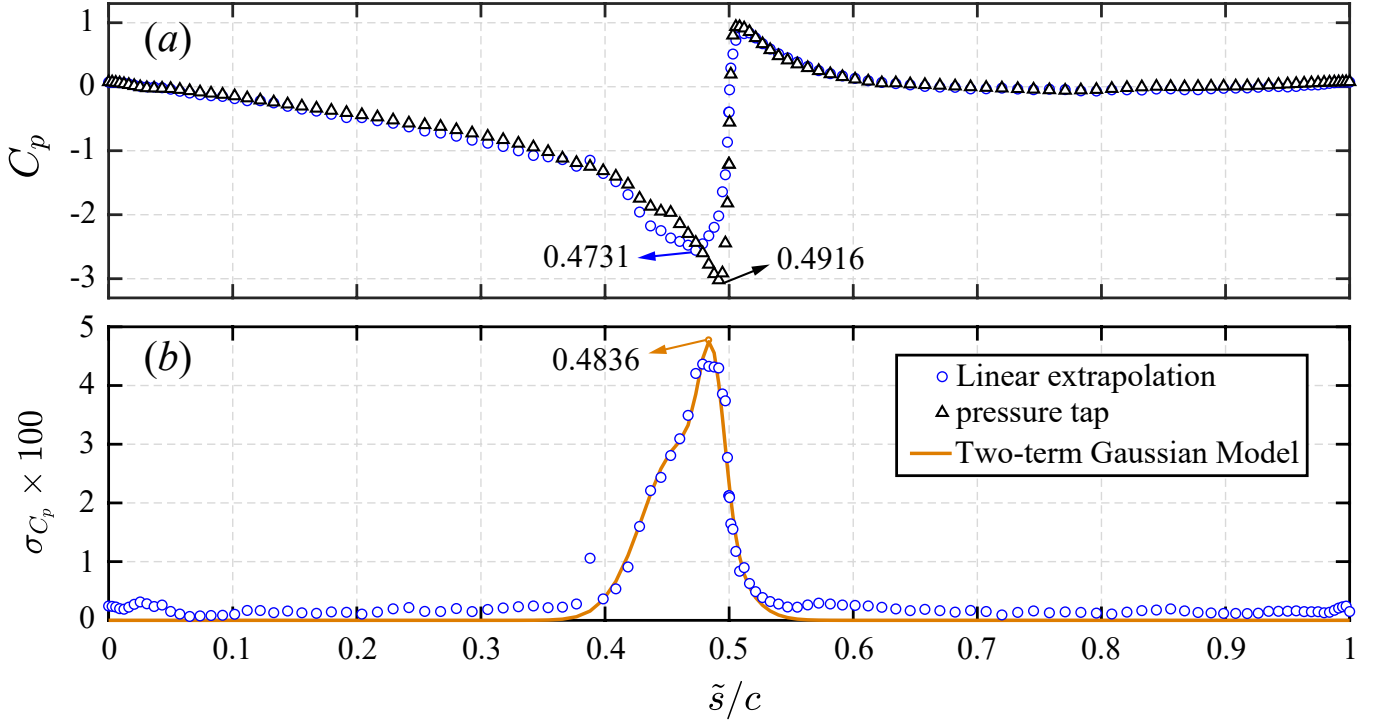


Figure 3. (a) Surface pressure coefficient obtained from pressure taps and from linear extrapolation of the PIV-based pressure field; (b) standard deviation of the surface-normal pressure-coefficient gradient.

3.2. Evaluation of the global constraint

Figure 4 compares the different terms of Eq. 8 evaluated on the boundaries of the control volume ABCD using the PIV velocity field and the reconstructed pressure field. The individual terms vary along the control-volume boundary, but their integrated contribution is nearly balanced. For the present case, the right-hand side of Eq. 8 evaluates to 0.036 in non-dimensional form, which is close to zero compared with the local variations of the individual terms. This result supports the use of the simplified global constraint given by Eq. 9 for the present steady airfoil case.

3.3. Reconstructed surface pressure

Figure 5 shows the final reconstructed surface pressure and its relative error with respect to the pressure-tap measurements. The proposed method effectively recovers the suction peak and provides a more accurate estimate of both its magnitude and location compared with direct linear

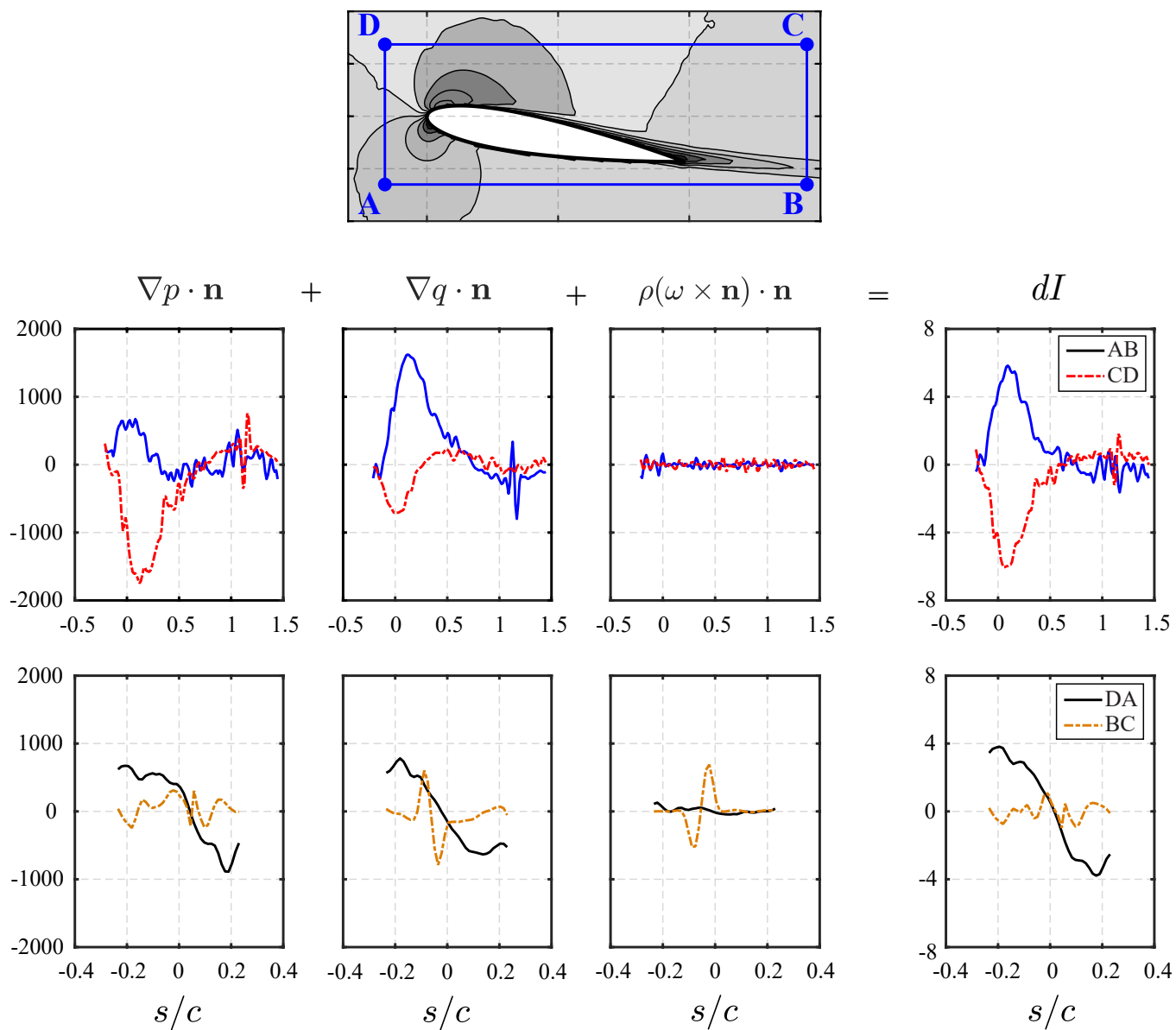


Figure 4. Evaluation of the different terms in the global constraint on the control-volume boundary. The integrated contribution is close to zero for the present steady airfoil case.

extrapolation. The improvement is most pronounced near the leading edge, where the extrapolated pressure is highly sensitive to the near-wall pressure-gradient behaviour. In this region, the proposed reconstruction reduces the error by approximately a factor of three. The reconstructed distribution also follows secondary features of the pressure curve, indicating that the B-spline representation and the physical constraints preserve relevant aerodynamic information rather than simply over-smoothing the solution.

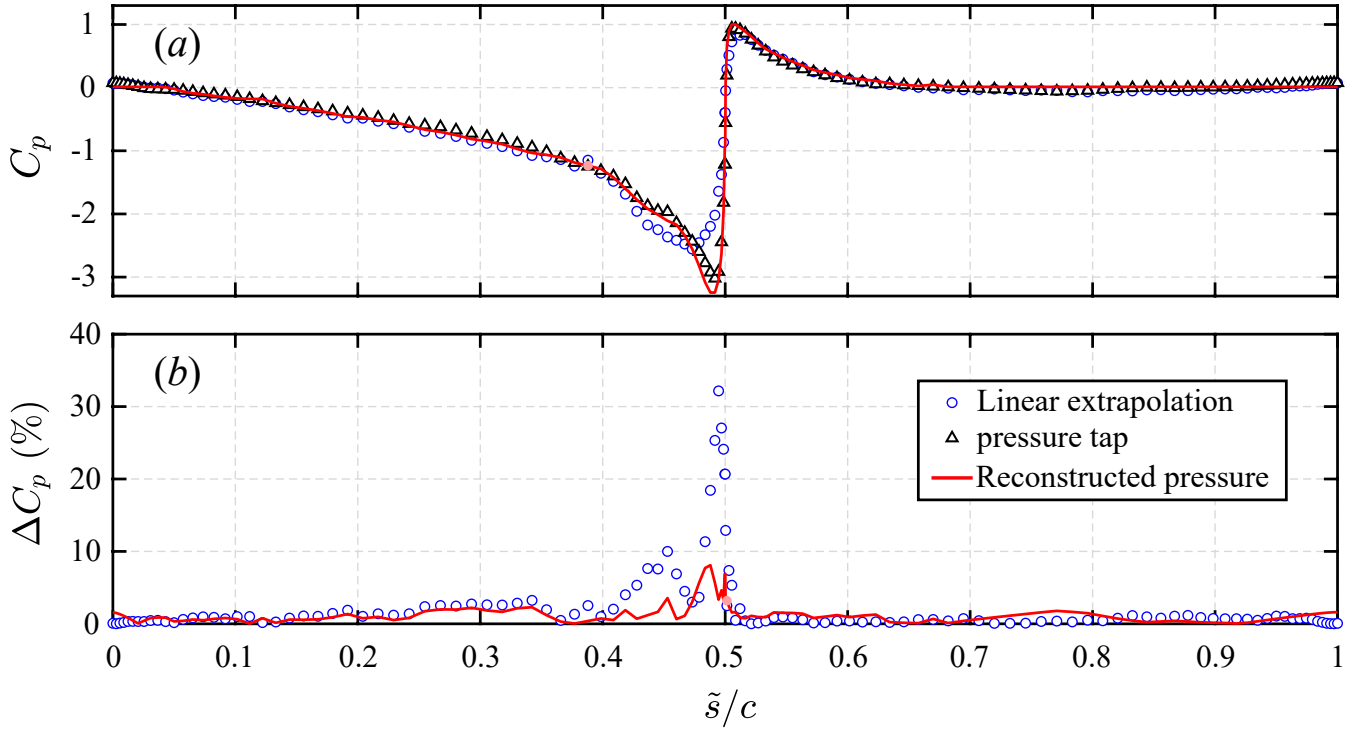


Figure 5. (a) Reconstructed surface pressure coefficient compared with pressure-tap data; (b) relative error of the reconstructed surface pressure coefficient.

Figure 6 compares reconstructed surface-pressure distributions obtained with and without the global constraint. In both cases, the local constraints and the σ_n -based weighting help recover the suction region. However, when the global constraint is omitted (Fig. 6 - a), the pressure distribution outside the suction-peak region remains biased towards the direct extrapolation. Including Eq. 9 reduces this bias and improves the consistency of the pressure distribution over the entire airfoil surface (Fig. 6 - b). This result shows that the global constraint is particularly important in regions where local extrapolation errors are not captured solely by the surface-normal pressure-gradient indicator.

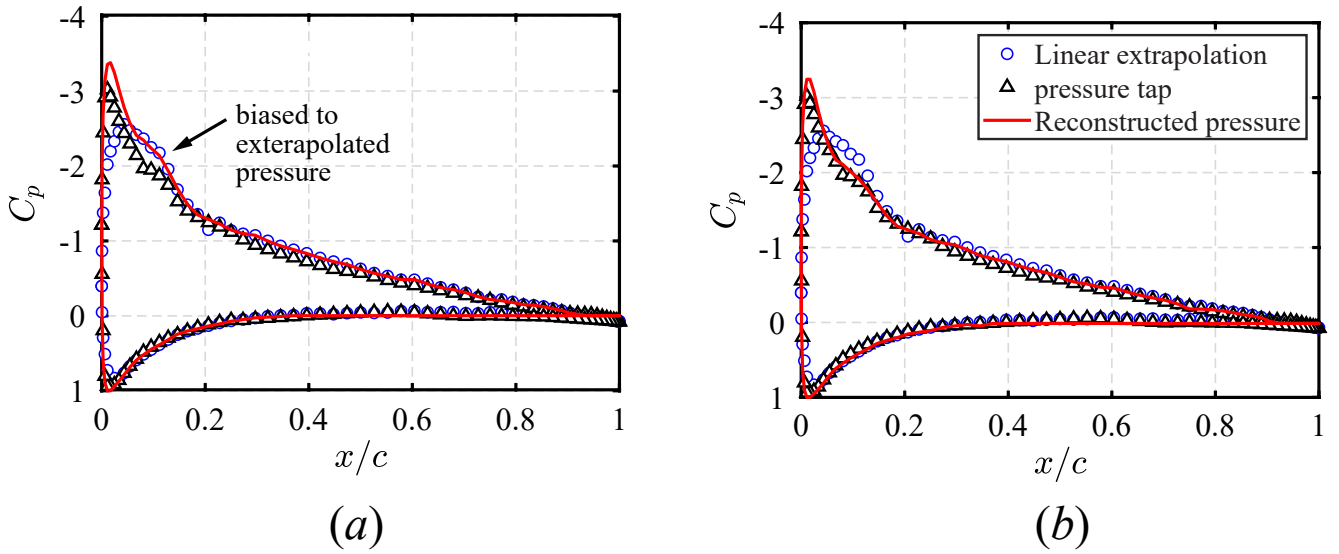


Figure 6. Effect of the global constraint on the reconstructed surface pressure coefficient: (a) reconstruction without the global constraint and (b) reconstruction with the global constraint.

4. Conclusions

A physics-informed method has been proposed for reconstructing surface pressure from PIV data. The method combines weighted least-squares optimization, B-spline representation of the surface pressure, local physical constraints, and a global balance constraint derived from the Navier-Stokes equation. The standard deviation of the surface-normal pressure gradient is used as a local uncertainty indicator and defines the spatial weighting of the optimization. This quantity also provides an objective way to identify the suction-peak location directly from the PIV-based pressure field.

Application to a NACA 0015 airfoil at $\alpha = 10^\circ$ and $Re_c = 2 \times 10^5$ shows that the proposed method significantly improves the surface-pressure reconstruction compared with direct linear extrapolation. The suction-peak location is identified with an error of approximately 1.5%, and the leading-edge pressure-reconstruction error is reduced by approximately a factor of three. The global constraint further improves the pressure distribution outside the suction region by reducing bias towards the extrapolated pressure. These results indicate that the proposed framework can enhance the reliability of PIV-based surface-pressure estimation, particularly in high-gradient regions that are critical for aerodynamic-load prediction.

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