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Assessment of drag prediction techniques based on radar data for supersonic vehicles

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Abstract. Flight testing is probably the most accurate approach for defining the aerodynamic characteristics of a flying vehicle. This is justified by the fact that compared to other approaches, either engineering or computational ones, flight testing is indeed the one that perfectly resembles the real flight environment. Flight data are either obtained by measuring the vehicle's kinematics via onboard sensors or by tracking the vehicle's flight via (commonly) radars. The advantages of the latter approach are evident in cases where modifying the vehicle design is not possible or in cases where rival/enemy vehicles are examined. The key issue for this approach is the quality and demands of the technique by which vehicle aerodynamic characteristics are reduced from flight-tracked data. In the open literature, different techniques are used to analyze radar data of vehicle position and utilize them to predict vehicle drag coefficient. Each technique has its strengths and pitfalls. In this paper, the three well-used techniques of drag estimation from radar data namely, Least Square (LS), Maximum Likelihood Estimation (MLE), and Stepwise regression (SR), are considered. The underlying principle, the output, and the range of validity for each technique are addressed with emphasis on what differentiates each of them. The viability and validity of the three techniques are addressed based on the own flight testing of a free-flight supersonic vehicle and using the point-mass flight model. Meteorological data are also recorded and flight conditions are used to enhance the resulting calculations. Based on experimental data available from the literature, a comparison is conducted for the techniques examined. Considering the lack of flight data utilized, and in conjunction with data from the literature, it has been concluded that the SR technique outperforms for a higher sample rate, however, the MLE is more feasible when there is a lack of data.

1. Introduction

Aerodynamic drag is one of the most significant factors that impact the vehicle flight performance namely its range. Less aerodynamic drag concludes higher vehicle range (or lower propulsion demands), which can be obtained by enhancing the vehicle airframe configuration dictated by the vehicle mission. Different techniques [1] are used to estimate vehicle drag among all other aerodynamic characteristics. They include theoretical approaches, numerical solutions using computational fluid dynamics (CFD), and experimental techniques. Theoretical approaches are based on empirical or semi-empirical equations as well as tabulated data reduced from basic theories or experiments on simple configurations. Examples include SPINNER [2], NSWCAP [3], MC-DRAG [4], MISSILE[5], AP98[6], DATCOM[6]. In contrast, computational methods [7-12] using CFD packages provide more accuracy and flexibility for non-conventional shapes and better insight into the physics of drag. Experimental techniques include wind tunnel [13-15], spark range [16-18], and flight test [13, 15, 19]; the latter is the most representative of the real nature of drag.

Drag is indirectly estimated from flight data. Estimation of drag based on flight data, a.k.a. data reduction, is conducted via a number of techniques [20-22]; requiring huge flight datasets including rounds with different launch conditions to accurately characterize drag in various flight conditions. Flight data are either measured or recorded during flight tests either via ground radar tracking or onboard sensors. The former-radar tracking- is the most convenient if modifications to the vehicle are infeasible. Focusing on various radar data reduction, numerous studies are available in the open literature [23-35] with different techniques had been developed. Chahan and Singh [36] collected and reviewed the majority of available techniques. Nonetheless, the most well-defined ones are the least-square, maximum likelihood estimation, and stepwise regression techniques.
The *least-square (LS) technique* was implemented to estimate drag for the 155mm M107 projectile in [23] and in [24] to investigate drag for the 155mm M549 projectile. The second technique, namely the *maximum likelihood estimation (MLE)* was applied through different studies to obtain drag for different aerial vehicles. Maine and Iliff [25] reduced the drag coefficient successfully for the T-37B airplane using flight data. In [27], MLE was implemented for a short-range tactical tail-controlled vehicle. Another study [26], was implemented to estimate the drag coefficient for the 130mm-Cargo projectile. For higher drag estimation accuracy, flight trajectory data were divided into sets with a constant time step.
The *stepwise regression (SR)* technique was applied in [13] for a modern fighter operating within an angle of attack range of 5-60 degrees to estimate its aerodynamic performance. Another study [28] was conducted to estimate the drag of aerospace vehicles via SR.
In the open literature, only a few studies (e.g., [36]) were devoted to assessing (viz-a-viz) the accuracy, demands, advantages, and disadvantages of flight data reduction techniques. More importantly, for the supersonic vehicle in concern, Hydra 70mm, drag reduced from radar data was briefly reported in [37]. The technique used (among other essential details) was not explained. These two aspects were the prime motivations of the present research.
This paper proposes a comparative study of the above mentioned techniques for estimating the variation of drag with flight Mach number (a.k.a, drag profile) for a case study vehicle based on flight data. The dependence of accuracy on the monotony of drag profile, dataset size, and model complexity is assessed. The remainder of the paper is organized as follows. The three drag estimation techniques are explained first. Then, the case study vehicle is introduced as well as the recorded radar data and the corresponding meteorological conditions. Next, results are discussed and compared with experimental data from the literature. Finally, the conclusion and forthcoming work are highlighted.

2. Drag prediction based on radar-tracked data

Based on radar-tracked flight data, the vehicle drag can be estimated using different estimation algorithms. In this study, three well-known techniques are implemented to explore the advantages and shortages of each one. In all, vehicle flight is defined by the point-mass PM flight trajectory model [23, 26]. The features of these techniques are explained below.

2.1. Least square (LS) technique

It is implemented by fitting the vehicle position $[x_{(t)} \quad y_{(t)} \quad z_{(t)}]^T$ in polynomial functions of arbitrary degrees and differentiating them twice to get the corresponding velocity and acceleration components $\mathbf{V}(t) = [v_x \quad v_y \quad v_z]^T, \mathbf{a}(t) = [a_x \quad a_y \quad a_z]^T$. Then, using these kinematics along with measured launch and meteorological conditions in the inverse PM trajectory model equation (1) under the action of earth's gravity $\mathbf{g} = [0 \quad -9.81 \quad 0]^T$ and the measured wind $\mathbf{W} = [w_x \quad 0 \quad w_z]^T$, the vehicle drag coefficient $C_D(t)$ as a function of Mach number $M(t)$ can be reduced as:

$$C_D(t) = \frac{-8\, m[(\mathbf{a}(t) - \mathbf{g}).(\mathbf{V}(t) - \mathbf{W})]}{\pi\, \rho\big(y_{(t)}\big)\, d^2\, V_\infty^3(t)} \tag{1}$$

$$M(t) = \frac{V_\infty(t)}{\sqrt{\gamma\, R\, T\big(y_{(t)}\big)}} \tag{2}$$

where, $\boldsymbol{m}$ is the vehicle burn-out mass**,** $\boldsymbol{d}$ is the vehicle caliber**,** $\boldsymbol{\rho}$ and $\boldsymbol{T}$ are the measured air density and temperature, respectively, and $\boldsymbol{V}_\infty = \sqrt{(\boldsymbol{v_x} - \boldsymbol{w_x})^2 + \boldsymbol{v_y^2} + (\boldsymbol{v_z} - \boldsymbol{w_z})^2}$ is the free stream velocity. LS requires data from multiple flights. In [23], 28 flight tests with different launch conditions were implemented.

2.2. Maximum likelihood estimation (MLE) technique

This is the most frequently used technique to estimate different parameters based on vehicle flight data. The flight dynamic model is implemented prior to applying ML. The drag coefficient is fitted as a polynomial function with n^{th} degree of the Mach number M as,

$$C_D(j) = c_0 + c_1 M + c_2 M^2 + \cdots + c_i M^i + \cdots + c_n M^n \tag{3}$$

Using *the maximum likelihood technique* [27]**,** the error between the measured and simulated trajectory parameters is iteratively minimized to estimate the polynomial coefficients of the proposed equation (3). The point mass model (PM) is utilized using equation (4) to simulate the trajectory of the projectile as,

$$\mathbf{a}(j) = -\frac{\pi\, \rho\big(y_{(j)}\big)\, d^2\, C_D(j)\, V_\infty(j)}{8\, m}(\mathbf{V}(j) - \mathbf{W}) \tag{4}$$

where, j is the instant position point and $j = [1 : no.of\ data\, points]$. Finally, the polynomial coefficients $(c_0, c_1, \ldots, c_n)$ are reduced at the end of each iteration until a minimum or a priorly defined error between the simulated and the measured data is achieved. This iterative process is implemented using the *genetic algorithm* GA [38, 39] which adds to the complexity and computational demands of the MLE technique.

2.3. Stepwise regression (SR) technique

Here, the rate of change of any measured parameter through any two successive measurements is assumed constant; i.e., linear variation. Hence, using the PM model, based on the vehicle position, the instantaneous vehicle elevation θ and azimuth ψ are computed as,

$$\theta_i = \tan^{-1}\left(\frac{\Delta \mathrm{y}}{\sqrt{\Delta \mathrm{x}^2 + \Delta \mathrm{z}^2}}\right) \tag{5}$$

$$\psi_i = \tan^{-1}\left(\frac{\Delta \mathrm{z}}{\Delta \mathrm{x}}\right) \tag{6}$$

Then, the instantaneous vehicle velocity components can be estimated as,

$$\mathbf{V}_i = \mathrm{V}_i.[\cos\theta_i \cos\psi_i \quad \sin\theta_i \quad \cos\theta_i \sin\psi_i]^T \tag{7}$$

Vehicle acceleration is computed by dividing the velocity difference of any two successive instances by the time step as:

$$\mathbf{a}_i = \frac{[\Delta v_x \quad \Delta v_y \quad \Delta v_z]^T}{\Delta t} \tag{8}$$

Finally, by substituting equations (7) and (8) in the inverse PM model proposed in equations (1) and (2), an estimation for the vehicle drag coefficient $C_D(i)$ as a function of Mach number $M(i)$ is obtained.

3. Case study and flight-test setup

In this study, the Hydra 70 mm [37] unguided air-to-surface tube-launched vehicle with three wrap-around fins WAFs is selected as the case study, Figure 1. The vehicle is composed of a blunt nose tip followed by an ogive-cylinder body. Both the vehicle boosting time and the corresponding burn-out velocity are about 1.05 s and 740 m/s, respectively. Different studies [37, 40] from the literature proposed the drag profile for this vehicle as shown in Figure 2. Chusilp et al [40]calculated the drag coefficient using the engineering technique "DATCOM" whereas Dahlke and Batiuk [37] deduced drag coefficient values at different Mach numbers from radar data; results of the latter will be used here for the sake of assessment of the examined techniques.

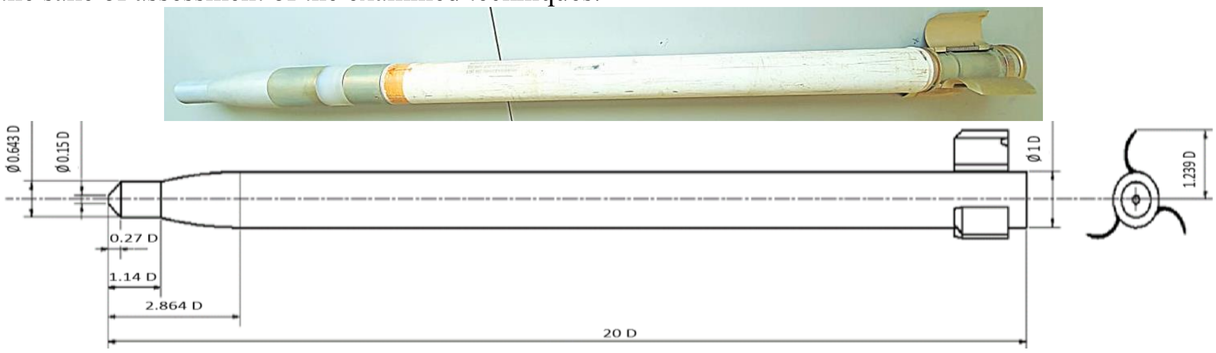

Figure 1 Case-study vehicle configuration and basic dimensions, $D = 70\ mm$.

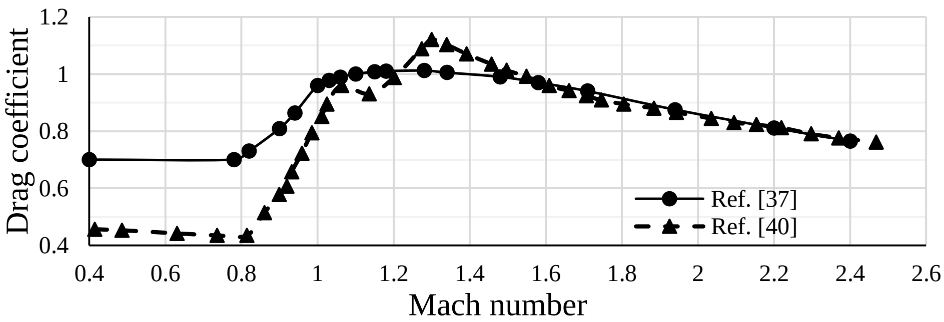

Figure 2 Case-study vehicle drag profile [37, 40].

Flight testing is conducted on the case study vehicle in a specialized firing range at a launch angle of 30°. Radar tracking range system ***MFTR-2100/40*** [41] is used and flight data are recorded with a sampling frequency of 1000 sample/s and then analyzed. The measured data include vehicle down range $x(t)$, altitude $y(t)$, drift $z(t)$, and velocity $V(t)$ through flight time t as illustrated in Figure 3. For accurate estimation of vehicle drag, meteorological conditions [42, 43] are measured including air temperature, pressure, density, and both the wind speed and direction referenced to the height above sea level as illustrated in Figure 4.

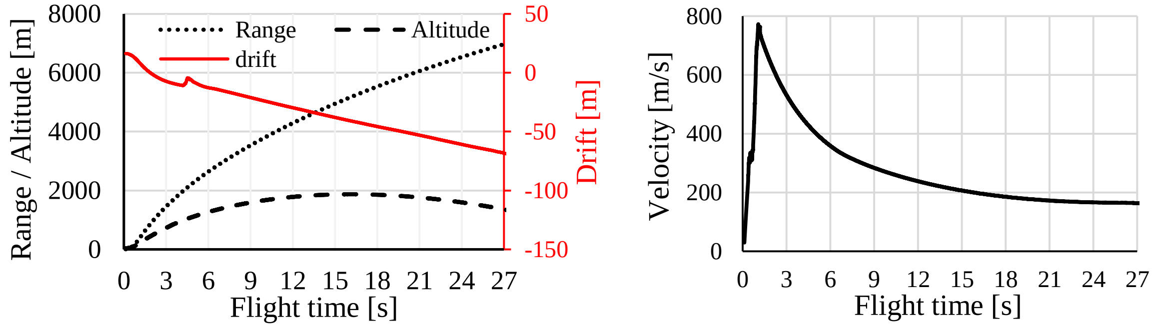

Figure 3 Vehicle flight trajectory features based on measured radar data.

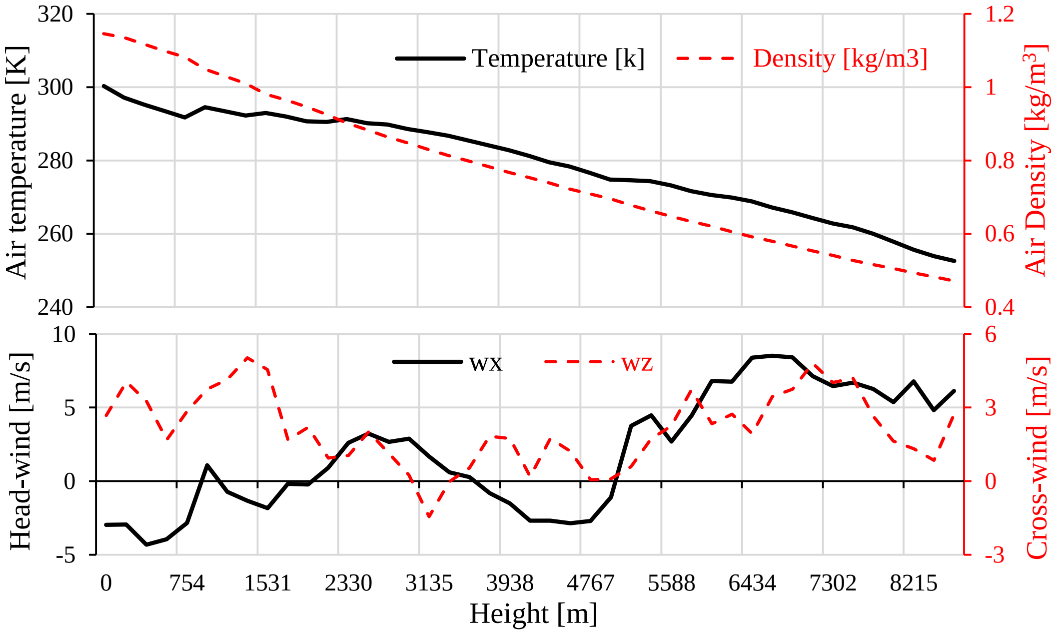

Figure 4 The measured meteorological conditions.

4. Results and Discussion

As the case study vehicle is an unguided fin-stabilized vehicle, the angle of attack is small enough that implementation of the point-mass model is assumed acceptable. Therefore, as a good approximation to the real trajectory, both the gravity and the aerodynamic drag forces are included considering flat, non-rotating Earth approximation. The radar data for the above experimental test is analyzed and reduced using three different techniques and the results are presented here. Only data beyond sonic speed through the coasting and the ascent flight phase are utilized for drag coefficient estimation to avoid the thrust effect. Assessment of the accuracy of the techniques is sought by comparing the reduced drag coefficient-Mach relation with that in [37], Figure 2.

As the drag profile has different (non-monotonic) patterns through different Mach regimes, two scenarios have been proposed dealing with the measured data as single- and two- datasets. In the single-dataset approach, the whole measured flight data are utilized to estimate a unified drag profile for the whole flight Mach regimes. In contrast, in the two-dataset approach, the measured flight data are divided into two datasets based on the flight Mach regimes namely the transonic regime (i.e. $1 < M < 1.2$) and the supersonic regime (i.e. $M > 1.2$) and hence, two separate drag profiles are reduced.

Firstly, applying the *least-square (LS)* technique, the case study vehicle drag coefficient is obtained as a function of the Mach number. Different trials were conducted to address the impact of (1) splitting the Mach range into two sets, (2) changing the fitting polynomial degree, and (3) reducing the sample rate of implemented data. It was found that neither Mach range splitting nor sample rate have an impact on the quality of drag estimation. In addition, the highest accuracy was attained using a third-degree polynomial. Figure 5 illustrates the comparison between the best-estimated results and the experimental data available from the literature [37]. Deviation of the estimated drag coefficient is evident, especially for the transonic and higher supersonic regimes.

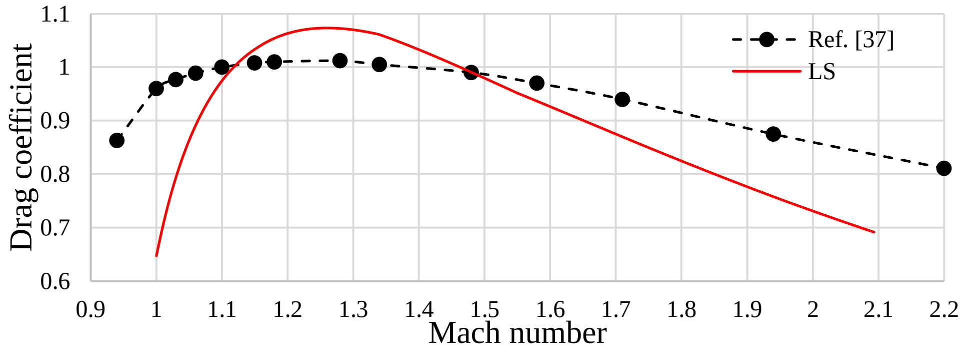

Figure 5 Estimated drag coefficient using the LS technique.

Secondly, applying the *maximum likelihood estimator (MLE)*, the vehicle drag coefficient as a function of Mach number is reduced based on the form of equation (3) assuming a second-degree polynomial function, where the equation coefficients are estimated by minimizing the cost function (i.e. root mean square error RMSE between measured and simulated data) using genetic algorithm GA. The impact of dataset splitting is evident in the MLE technique. As illustrated in Table 1, the two-datasets solution outperforms the single-dataset one as the RMSE is reduced resulting in a better fit of the simulated data to the measured ones as shown in Figure 6. Similar to the LS technique, polynomial degree and sample rate were found to have no impact on the accuracy of MLE accuracy.

Table 1 The Results obtained using MLE.

No. of phases	Mach no.	c_0	c_1	c_2	RMSE
One phase	*M > 1*	0.776	0.3429	-0.1447	0.696
Two phases	*1 < M < 1.2 (transonic)*	-0.3046	1.872	-0.6534	0.0083
	M > 1.2 (supersonic)	1.125	-0.083	-0.016	0.0843

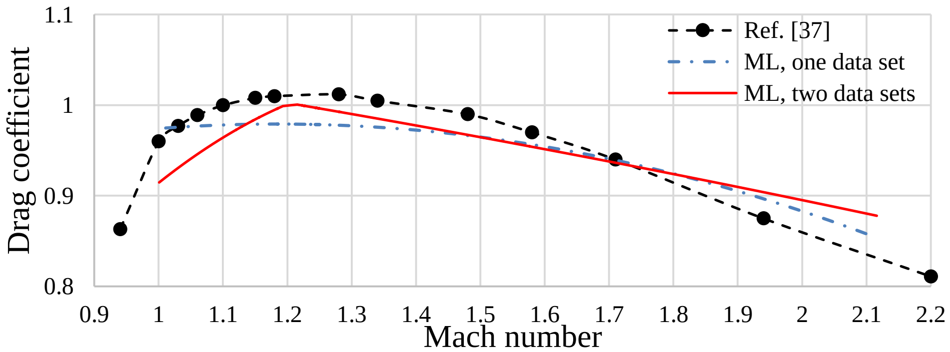

Figure 6 Estimated drag profile using the MLE technique.

Finally, the *stepwise regression (SR)* technique is implemented. One feature of this technique is that its accuracy is dependent on the sampling rate. Therefore, an investigation is performed to examine the impact of changing the data sample rate on vehicle drag profile including 2, 10, 100, and 1000 samples per second (referred to as SR1, SR2, SR3, and SR4, respectively). Figure 7 shows the vehicle drag coefficient as a function of the Mach number for different data sampling rates. It is obvious that the resulting accuracy is sensitive to the given number of samples along the flight. In contrast, splitting the dataset was found to have an insignificant impact on the accuracy of drag estimation.

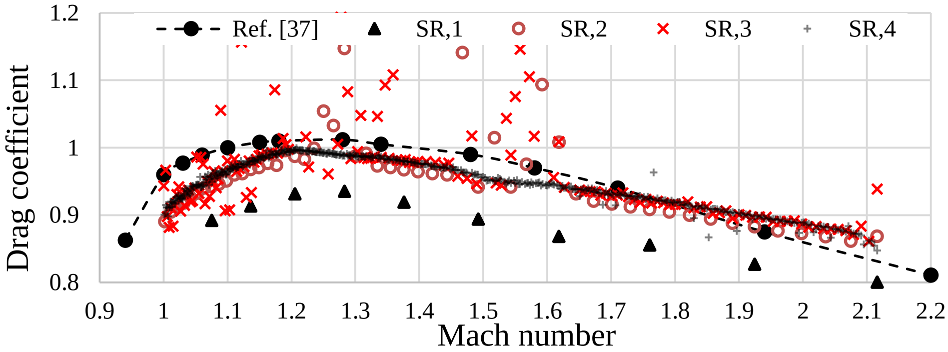

Figure 7 Estimated drag coefficient using SR technique for different sample rates.

To wrap up, the resulted drag coefficient of the three techniques are compared in Figure 8 along with published results [37]. The drag profile estimated via the LS technique is the least accurate with a RMSE of ***0.123***. The drag profile for the maximum likelihood technique (ML) with two datasets and the stepwise regression technique (SR) with a rate of 1000 samples/second are almost coincident. The RMSE values of these two techniques are ***0.0324*** and ***0.0421***, respectively. Deviation from [37] may be due to other aspects e.g., measurement tolerances, and radar system features. The drag estimation technique adopted in [37] was not stated. All RMSE in drag profiles based on the aforementioned drag estimation techniques are listed in Table *2*.

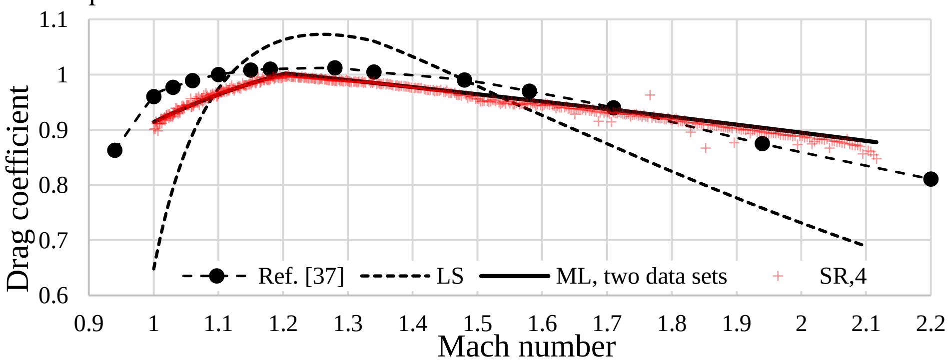

Figure 8 Comparison of different drag estimation techniques.

Table 2 RMSE in drag profiles.

Technique	RMSE
Least square (LS)	0.123
Maximum likelihood (ML, two data sets)	0.0324
Stepwise regression (SR4, 1000 samples/second)	0.0421

5. Conclusion

Estimating drag from flight data is one of the most accurate approaches. However, the estimation accuracy is dependent on a number of aspects including the complexity of the used technique, flight dataset size, and flight regime variations. In the present paper, A comparative study of three well-

defined, widely-used techniques is conducted for a free-flight unguided supersonic vehicle as a case study. These techniques include the *Least Square*, *Maximum Likelihood Estimation*, and *Stepwise Regression*. The impact of technique complexity, sampling rate, and flight regime variation on accuracy and cost of drag estimation is highlighted.
For the case study examined, results showed that the least square technique yields the least estimation accuracy based on a single flight. More flights would yield higher drag estimation accuracy. For the MLE technique, splitting the measured flight data into multiple sets based on the flight Mach regime improves estimation accuracy that is independent of sampling rates. MLE is generally more computationally expensive yet shows high accuracy even with low sample rates, i.e., less flight-demanding. In contrast, SR is less computationally sophisticated however, its accuracy is sensitive to the sampling rate. Low sampling rates would yield low drag estimation accuracy.

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