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Four-Channel Suction Distribution Optimization Experiments for Laminar Flow Control

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Further developments of a system for smart suction management for hybrid laminar flow aircraft are presented, wherein the energy saved by reducing drag must be balanced against the energy expended in providing the suction. Experimental results are presented, whereby the streamwise distribution of suction velocity over a flat plate in a wind tunnel is automatically adjusted so that the laminar–turbulent transition point, which is detected by an array of surface-mounted microphones, is maintained at a desired point and the suction pump energy required to keep it at that point is minimized.

Nomenclature

D	= distance between microphones
e	= transition position error
g	= pump energy cost
J	= Lagrangian function
k	= time step index
M	= number of microphones
N	= number of suction panels
$\langle p \rangle$	= rms average pressure
r	= desired transition position
T	= averaging time for rms measurements
U_∞	= mean flow velocity
u_i	= ith suction velocity
$\boldsymbol{u}^*$	= optimum suction vector
v_i	= ith pump control voltage
y	= distance from leading edge to transition
α	= error reduction parameter
λ	= Lagrange multiplier
μ	= step size parameter

Introduction

IT is well known that relatively small amounts of suction applied to the laminar part of a boundary layer can significantly delay the transition to turbulence and, hence, reduce drag. If a transport aircraft were to be designed from the outset to take advantage of this effect, it could have very low drag indeed.[1] This is particularly true if the engine size could be reduced because less propulsion would be needed in cruise, and the fuel load could be reduced because less fuel would be needed. In practice, this is unlikely to become a reality in the near future for two reasons. First, the economics of transport aircraft dictate that radically new designs are unlikely in the near future and that new models will continue to be derivatives of past, proven designs. Second, to take advantage of the potential savings in engine size and fuel weight, the suction system would have to be guaranteed to produce the promised drag reductions regardless of conditions. For these reasons the aircraft most likely to use suction first will probably be similar in configuration to existing designs but use suction in combination with naturally laminar geometry, that is, hybrid laminar flow.[2] Under these conditions the savings in drag will be much lower than that which the ideal theory might predict and may well be low enough that the energy spent in providing the suction will be an appreciable fraction of the propulsive energy saved through the reduction in drag.[3] In fact, it could, in principle, be larger. This has been shown for the idealized case of a flat plate with uniform localized suction[4]: As suction is increased, the total energy required to overcome drag falls, reaches a minimum, and then increases.

In many commercially proposed flight test implementations of hybrid laminar flow control, multiple suction panels are used, a typical example being the Airbus A320 hybrid laminar flow fin.[5] This paper addresses the problem of determining the optimal suction distribution on such a multiple-panel system so as to minimize overall energy consumption. To determine the optimal transition position for the boundary layer, it is necessary to be sure that the minimum amount of energy is being spent on suction at every trial transition point. Furthermore, there may be overriding aerodynamic considerations (such as the necessity of avoiding separation) that constrain the transition point. In either case, there is a necessity for a procedure to determine the optimal suction distribution that maintains a given transition position for the minimum expenditure of suction-pump energy. A preliminary investigation of this problem was given in a previous paper[6] for the case of a wind-tunnel model with two independent suction panels. An algorithm was presented that can adaptively solve the constrained optimization problem, that is, minimize pump energy subject to the constraint that the transition be maintained at the desired point. In this paper the results of experiments on another model having four streamwise suction panels are presented. It is shown that the same essential algorithm can optimize the four-channel suction distribution but that a significant modification to the Lagrange multiplier update strategy is necessary if the system is to remain stable. With four suction panels it is possible, for the first time in an experimental context, to see how the shape of the optimal suction distribution varies with the desired transition position. It is also possible to optimize suction off-line by the use of a suitable computational fluid dynamics transition prediction scheme. This has been implemented by Balakumar and Hall,[7] using a procedure that, in contrast to that described here, maximizes transition delay for a given expenditure of suction energy.

Optimization Problem

The formulation of the constrained optimization problem has been given in some detail[6,8] but will be briefly recapitulated for easy reference. The speed of the pumps is controlled by a vector of control signals $\boldsymbol{v}^T$ that induces a vector of suction velocities given by $\boldsymbol{u}^T = (u_1, u_2, \ldots, u_N)$ numbered from leading edge to trailing edge. The dependence of the suction velocities $\boldsymbol{u}$ on the pump control signals $\boldsymbol{v}$ is sufficiently close to linear, and $\boldsymbol{u}$ and $\boldsymbol{v}$ are sufficiently independent of each other that there is a one-to-one mapping between the two. This means that it is sufficient to optimize the control signals and measure the corresponding suction velocities to find the optimal suction velocities.

For a given, fixed mean flow velocity, each suction distribution $\boldsymbol{v}$ will result in a laminar–turbulent transition position $y(\boldsymbol{v})$ and will consume suction pump energy $g(\boldsymbol{v})$. To place the transition position so as to maximize the overall energy saving, it is necessary, at every candidate position, to adjust the suction distribution so

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as to minimize the energy cost required to achieve that transition position. We, therefore, have a constrained optimization problem for every desired transition position r: Minimize $g(\boldsymbol{v})$ subject to $e(\boldsymbol{v}) = y(\boldsymbol{v}) - r = 0$, where $r = 0$ corresponds to $y = 0$. If the solution to such an optimization problem is denoted by $\boldsymbol{v}^*$ with corresponding optimal suction velocity distribution $\boldsymbol{u}^*(\boldsymbol{v}^*)$, then for every multiple-panel suction system there will be a family of optimal suction distributions $\boldsymbol{u}^*(r)$ that will, in turn, depend on pressure gradient, etc. The most idealized case of such a family of problems might correspond to a flat plate and a quadratic cost function that we have previously considered.[6,8] It is unrealistic, however, to expect to be able to draw general conclusions from the optimal distributions obtained in this case because changing either function would require a new set of optimal distributions to be calculated. The response function $y(\boldsymbol{u})$ would change with, for example, mean flow speed, the pressure distribution over the body, the location of the suction panels, and so on. Although it is useful to be able to determine the most efficient place on the aircraft to apply suction, for a retrofit solution the feasible locations for suction panels may be severely constrained. Furthermore, some factors, such as the pressure gradient, may change during flight. Similarly, the true cost effectiveness of the suction strategy depends on an accurate model of the energy cost $g(\boldsymbol{u})$ associated with each suction distribution, and if this changes (which it may do with temperature, for example), then the optimal suction distribution may also change. For these reasons an adaptive scheme has been developed that continually updates $\boldsymbol{v}$ so as to track the optimal suction distribution.

Note that, although we can reasonably assume that $\partial y/\partial v_i \geq 0$ and $\partial g/\partial v_i \geq 0$ for all i, this is not enough to guarantee that the family of optimization problems will not have local optima, and for this reason so-called novel algorithms have been tested on this problem, in particular simulated annealling and genetic algorithm.[9]

Optimization Algorithm

As previously expounded,[6,8] the optimization problem can be iteratively solved by forming the Lagrangian function at the kth iteration:

$$J(\boldsymbol{v}) = g(\boldsymbol{v}) + \lambda e(\boldsymbol{v}) \tag{1}$$

by using an estimate of the Lagrange multiplier given by

$$\hat{\lambda}_k = \frac{-\mu \nabla g_k^T \nabla e_k + (1 - \alpha) e_k}{\mu \nabla e_k^T \nabla e_k} \tag{2}$$

and minimizing the Lagrangian by steepest descent:

$$\boldsymbol{v}_{k+1} = \boldsymbol{v}_k - \mu \nabla J_k \tag{3}$$

The parameter μ determines the step size for the gradient descent, and the parameter α determines the relative importance of minimizing e and g.

It has been found experimentally that the Lagrange multiplier estimate can be extremely sensitive to noise in the measurement of the error gradient ∇e. Therefore, in the experiments reported here, the Lagrange multiplier estimate was updated according to

$$\lambda_k = (\lambda_{k-1} + \hat{\lambda}_{k-1})/2 \tag{4}$$

This has the effect of damping out errors in the estimate of the Lagrange multiplier because any deviation from the current value would have to be persistent to permanently change the value of λ used for the update. The effect of this improvement is demonstrated in the Results section. Furthermore, because Eq. (2) is singular for $\nabla e_k = 0$, the Lagrange multiplier was not updated at all if $\nabla e_k^T \nabla e_k$ fell below a suitably chosen threshold value. Finally, the suction pump voltages were hard limited at values corresponding to suction velocities of 0 and 0.05 ms^{-1}; any values outside this range were clipped to the appropriate limit.

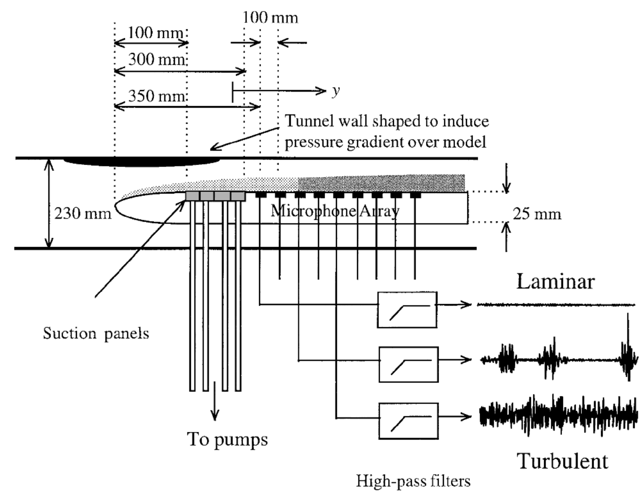

Fig. 1 Diagram of the flat plate with embedded suction panels and microphones.

Experimental Arrangement

The algorithm was tested on an aluminum, 1100 × 230 × 25.6 mm flat plate, with an elliptical leading edge 100 mm long, followed by four adjacent, identical suction panels, faced with a 200-mm continuous sheet of laser-drilled porous titanium sheet, having 0.1-mm-diam holes randomly spaced by 1 mm, giving an open area of 0.78%, supplied by Aerospace Systems and Technologies.

Connections were provided to both sides of the suction panels to aid in uniform suction distribution over the whole span of the porous surface. Each of the individual suction panels was connected to an Esam Uni-Jet 40 CE 250-W side-channel aspirator pump via a Microbridge AWM5103V airflow sensor. The speed of each pump was controlled from a personal computer via a Eurotherm type 601 three-phase inverter. The experimental apparatus is shown in schematic form in Fig. 1. The pump speed control voltages $\boldsymbol{v}$ were scaled so that a range of 0–5 V corresponded to a suction velocity range of approximately 0–0.05 ms^{-1}.

The plate was installed in a wind tunnel having a 0.305 × 0.23 m (11 × 9 in.) working section, 1.5 m in length. The maximum flow velocity that could be produced in the working section was 20 ms^{-1}, and the associated turbulence level was about 0.8%. For the experiments reported here the mean flow velocity was 10 ms^{-1}. The walls of the tunnel were shaped as shown to place the suction panels in an adverse pressure gradient.

The transition position was monitored by the use of surface-mounted Panasonic electret microphones (permanently charged condenser microphones) as described in previous work.[10,11] The microphone signals were high-pass filtered at 800 Hz to remove the noise from the wind-tunnel fan and then sampled at 5 kHz for 2 s. The estimated displacement of the transition position of the boundary layer was obtained from

$$y_k = \left[M - \sum_{m=1}^{M} \frac{\langle p(m) \rangle_k}{\langle p(m) \rangle_0} \right] D \tag{5}$$

where $\langle p(m) \rangle_0$ is the rms pressure fluctuation on microphone m when no suction is applied and D is the distance between microphones. This expression effectively counts the number of microphones that have been silenced by the suction. (In reality, of course, the microphones detect pressure fluctuation pseudosound rather than true sound.) Previous studies of this technique of transition estimation[12,13] have shown that this technique is reliable for a flat plate experiment. Note that, when the body has a significant pressure gradient, the level of pseudosound power measured beneath the turbulent boundary layer just after transition is significantly higher than that measured farther downstream. The technique can still be used in these situations, but it is then necessary to apply a threshold function to the microphone rms levels to remove this source of bias and, therefore, to increase the number of microphones to achieve the same resolution. In other words, each microphone is effectively an on–off turbulence detector. In the experiments reported here, six microphones spaced 100 mm apart were monitored, the first microphone being located 50 mm downstream of the last suction panel. The conceptual origin of the transition diplacement y is, therefore, 50 mm upstream of the downstream edge of the last suction panel (Fig. 1). The nature of the transition estimation procedure dictates that this variable cannot be unambiguously interpreted as a transition position when either all of the microphones are silent or all of the microphones are noisy. The useful operating range of the system is, therefore, from 0.1 to 0.5 m from this origin. The simplified model g of the energy cost used was the sum of the squares of the suction velocities, as measured by the airflow sensors. The gradients ∇e and ∇g were estimated by altering the suction velocity at each panel in turn by ± 0.004 ms^{-1} and measuring the resulting changes in e and g.

The specified accuracy of the flowmeters was $\pm 3\%$ of their reading, and the pump control system adjusted the pump speed until the flowmeter reading was within 1% of the required value. The transition estimations were repeatable, with a standard deviation of 1 cm.

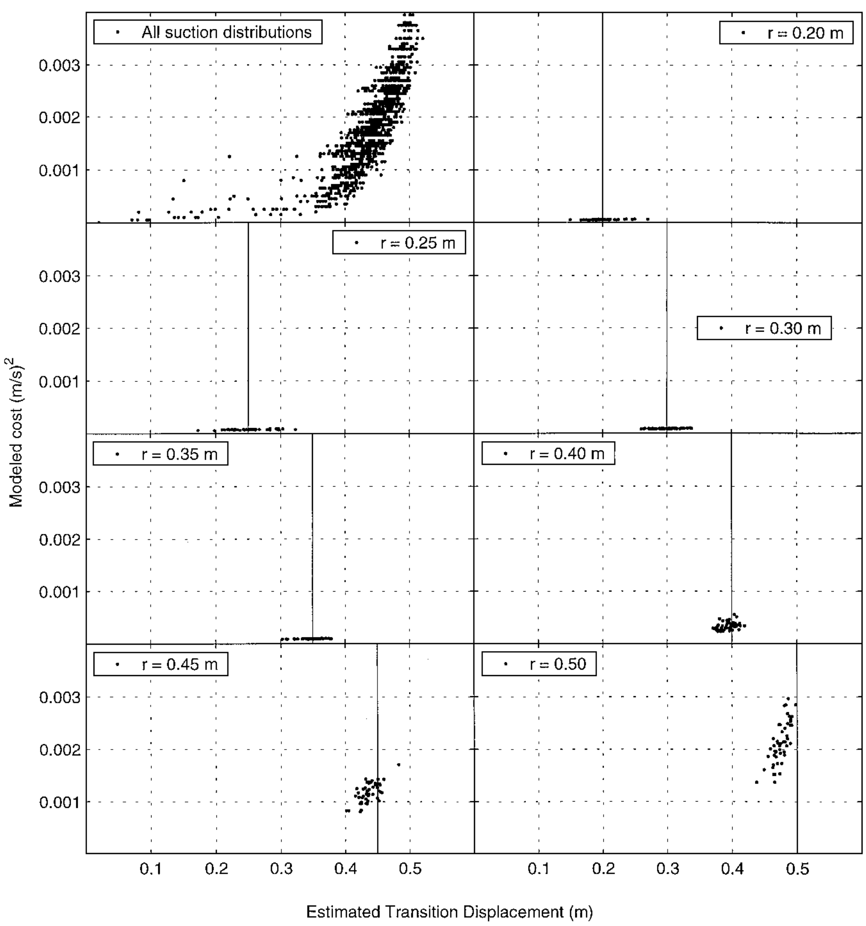

Fig. 2 Transition delay vs cost scatter for an exhaustive range of distributions (top-left-hand panel) and for settled controller (subsequent panels); the modeled cost is identical to the pump energy function $g(v)$.

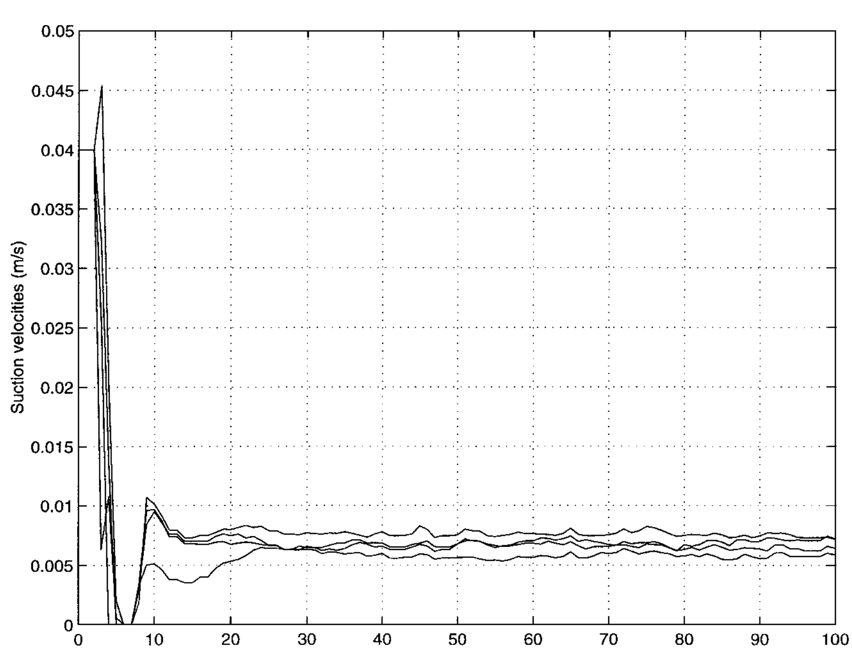

Fig. 3 Development of suction distribution induced by the algorithm when $r = 0.2$ m, that is, time histories of the four suction velocities superimposed.

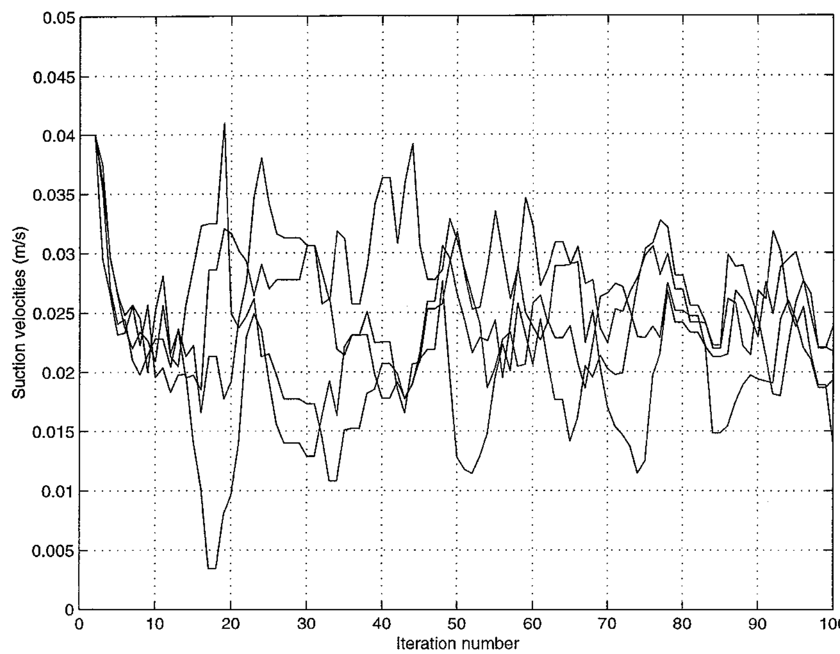

Fig. 4 Development of suction distribution induced by the algorithm when $r = 0.4$ m.

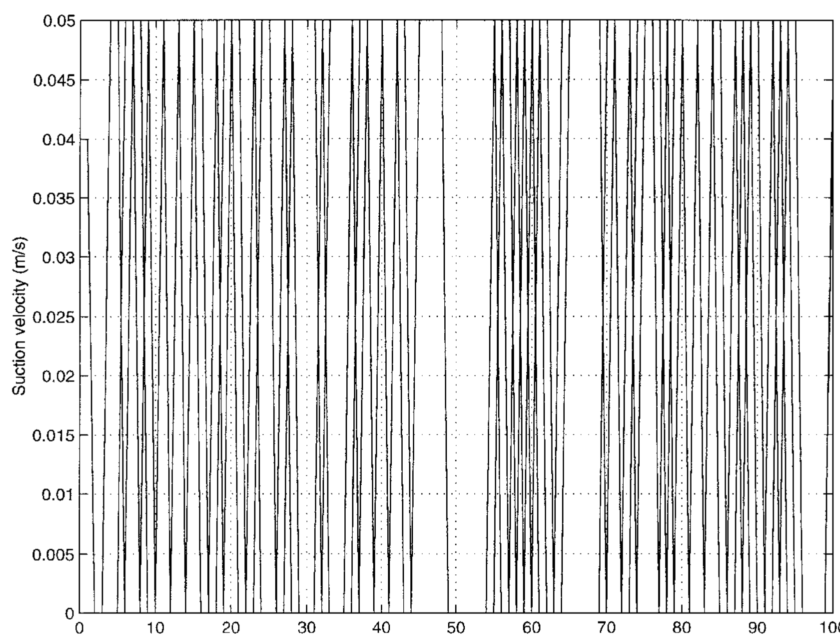

Fig. 5 Development of suction distribution induced by the algorithm when $r = 0.2$ m but without Lagrange multiplier damping.

Results

Each suction panel was stepped through six levels of pump speed, corresponding to an approximate range of suction velocities from 0 to 0.05 ms^{-1} so that $6^4 = 1296$ different suction distributions were applied. For each of these, the transition position and energy cost was recorded, and they are plotted against each other in the first panel of Fig. 2. The bottom edge of this cloud of points, therefore, indicates the minimum energy cost needed to achieve each transition position. The ratio of the top edge to the bottom edge at any horizontal position gives the potential energy savings available through the use of distribution optimization. The goal of the optimization algorithm (in terms of this graph) is to seek out the lowest point within the cloud on a given vertical line whose horizontal coordinate is the desired transition position.

The algorithm was then run seven times, each time with a different value of desired transition position. Each run consisted of 100 iterations; at the starting point in each case, 4 V was applied to each pump speed controller, corresponding to an approximate suction velocity distribution of $\boldsymbol{u}^T = (1, 1, 1, 1) \times 0.04\,\text{ms}^{-1}$. At this point, λ was updated only if $\nabla e^T \nabla e$ was greater than 500. In the subsequent panels of Fig. 2, the attained values of transition and cost are plotted against each other for the second 50 iterations of each run, and the desired transition r is shown by a vertical line.

Figures 3 and 4 show time histories of the suction velocity profile for the trials with $r = 0.25$ and 0.4 m, respectively. Figure 5 shows a similar time history for a trial without the Lagrange multiplier being damped, that is, with the multiplier updated according to $\lambda_k = \hat{\lambda}_{k-1}$ instead of Eq. (4).

Figure 6 shows the suction distributions chosen by the algorithm for each value of r, that is, an estimate of $\boldsymbol{u}^*(r)$. For reasons discussed hereafter, these are the averages of the last 30 suction distributions.

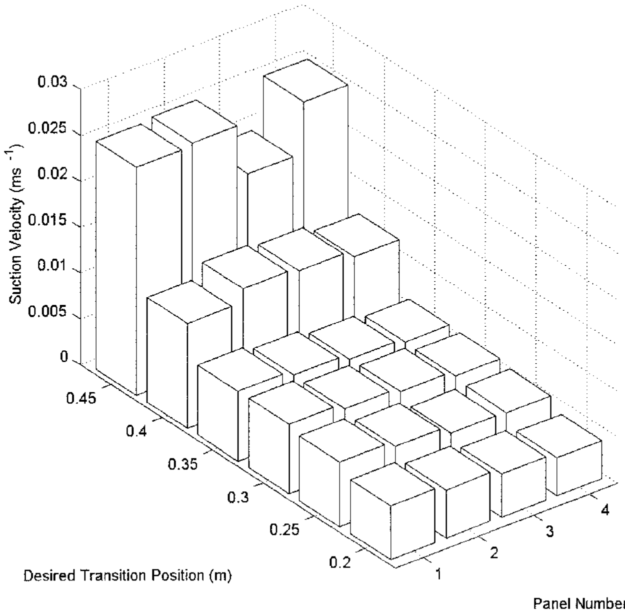

Fig. 6 Estimated family of optimal suction distributions $u^*(r)$ found by averaging the last 30 iterations of the algorithm for each trial.

Discussion

A comparison of Figs. 3 and 5 shows that the damping of the Lagrange multiplier [Eq. (4)] is effective in preventing sudden disturbances to the controller state.

Figure 2 shows that the algorithm is capable of maintaining the transition at or close to a desired point while minimizing the suction energy required to do so. The relative variation in transition and cost varies with r. When r is small, the transition point is very sensitive to suction so that a small change in $\boldsymbol{u}$ causes a large change in y. Furthermore, there are relatively few suction distributions that produce such a small transition delay, and so for the case $r = 0.25$ m, for example, the variation in y is larger than the standard deviation for steady suction. This is because equality-constrained optimization problems are necessarily ill conditioned at their optima, where the constraints are parallel to the cost contours,[14] as can be readily seen in the two-dimensional results presented previously.[6] This causes the system to hunt at an optimum. It would be simple, in practice, to modify the system so that once it was sufficiently close to an optimum it stopped adapting. Nevertheless, the variation in u once the algorithm has converged and hence the variation in g are both small.

Because of the relatively small number of steps in suction velocity taken on each panel to produce the first panel of Fig. 2, the suction distributions reached by the algorithm for lower values of r actually lie outside the envelope of all suction distributions used to produce Fig. 2. In other words, even a search through 1296 different suction distributions did not find as efficient a suction distribution as 30 iterations of the algorithm.

When $r = 0.4$ m, however, there are many different suction distributions capable of producing the desired transition, and the variation in y is small. Still, the variation in $\boldsymbol{u}$ shown in Fig. 4 is significant, suggesting that the system is wandering between two states. The corresponding scatter diagram in Fig. 2, however, shows that moving between the states is not apparently detrimental to either the maintenance of the transition or the minimization of the energy cost.

Because of this potential wandering effect, the optimal suction distribution $\boldsymbol{u}^*$ chosen by the algorithm was taken to be the average of the last 30 samples rather than the final value given. Figure 6 shows that this optimum does not scale linearly with the desired transition position r, which indicates the desirability of such an optimization procedure to maximize the efficiency of practical implementation.

Conclusions

A procedure for optimizing the distribution of suction so as to minimize the suction energy used to provide a given level of transition delay and, hence, drag reduction has been presented and successfully demonstrated in a series of experimental results. The previously presented optimization algorithm has been modified by the addition of Lagrange multiplier damping, and this has been shown to prevent potentially undesirable behavior of the algorithm and to enhance its suitablity for this class of problems. A new and important, though unsurprising, result is that the family of optima for this problem is not merely linear scalings of one distribution, that is, the optimal distribution changes shape as well as magnitude as the transition point is moved farther back.

In future work we propose to implement the procedure on a larger wind-tunnel model that will be capable of providing absolute drag force measurements as well as transition position estimates. In this way the algorithm can be used to explore the true power balance and fully optimize the energy savings promised by the application of suction in a manner applicable to full-scale aircraft demonstration.

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