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## Sound simulation-based design optimization of brass wind instruments

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1           We present a method for optimizing the inner shape of brass instruments using sound  
2 simulations. This study considers different objective functions and constraints (representative of both the intonation and the spectrum of the instrument) for a relatively large  
3 number of design variables. A complete physics-based model, taking into account the instrument and the musician embouchure, is used to simulate permanent regimes of sounds  
4 by means of the harmonic balance technique, the instrument being represented by its input  
5 impedance. The design optimization variables are related to the geometrical dimensions of  
6 the resonator. The embouchure's parameters are varied during the optimization procedure  
7 to obtain an average behavior of the instrument. The objective and constraint functions of  
8 the optimization problem are evaluated using the physics-based simulation model, which is  
9 computationally expensive. Moreover, the gradients of the objective and constraint functions  
10 can be discontinuous, unavailable, or hard to approximate reliably. Therefore, we  
11 employ a surrogate-assisted derivative-free optimization strategy using the mesh adaptive  
12 direct search algorithm (MADS). One example of a Bb trumpet's bore is used to demonstrate  
13 the effectiveness of the design optimization approach: the obtained results improve  
14 previously reported objective function values significantly.  
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17 **I. INTRODUCTION**

18 The development of innovative and higher-quality designs is crucial to the viability of musical  
 19 instrument manufacturers. Many prototypes are required to ensure that quality attributes such as  
 20 intonation, ease of emission, timbre, projection, etc. are adequate at each stage of the develop-  
 21 ment process. Numerical acoustics models may be helpful in shortening development cycles by  
 22 minimizing the manufacturing of costly prototypes. For example, in the case of brass instruments,  
 23 several studies propose the use of numerical modeling to predict quality and guide the design  
 24 process (Campbell, 2004; Macaluso and Dalmont, 2011).

25 The dominant physical quantity impacting the sound quality of a brass instrument is its input  
 26 impedance (cf. Figure 1). Input impedance is the frequency-dependent quotient of pressure and

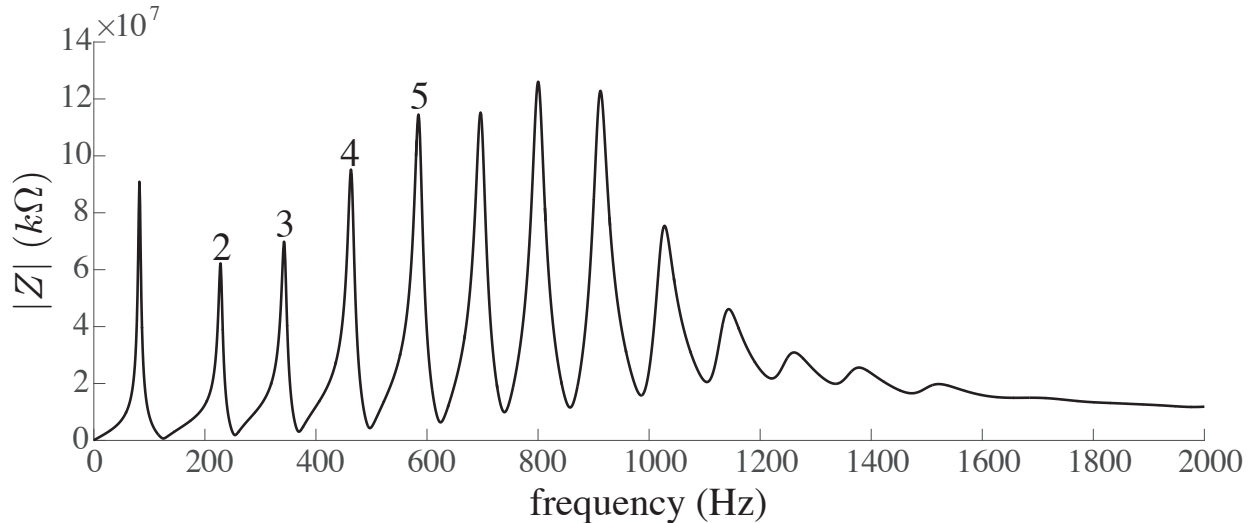


FIG. 1. Simulated input impedance  $Z$  of a Bb trumpet (magnitude), highlighting resonances 2, 3, 4, and 5  
 of the instrument

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29 volume flow at the instrument entry plane, and, at first approximation, is the result of the in-

30 **strument's interior shape (the bore)**. Many works have focused on modeling input impedance,  
31 e.g., (Caussé *et al.*, 1984).

32 The impact of input impedance on sound quality is acknowledged in (Campbell, 2004), where,  
33 in a first approximation attempt, playing frequencies are governed mainly by corresponding  
34 impedance peaks (Eveno *et al.*, 2014). Beyond influencing the instrument intonation, impedance  
35 also determines an instrument's timbre and **playability**, notably due to the height and bandwidth  
36 of peaks.

37 With this in view, several researchers have used input impedance to design an instrument's inner  
38 shape using an optimization approach. Following Kausel's successful reconstruction of a trumpet  
39 bore using the Rosenbrock algorithm (Kausel, 2001), Noreland optimized the instrument's intona-  
40 tion with a hybrid scheme for the input impedance model and shape constraints (Noreland *et al.*,  
41 2010). Braden also optimized the intonation and the input impedance **peak heights** of a trombone  
42 using a multi-modal input impedance model (Braden *et al.*, 2009), while **Macaluso** optimized and  
43 built a near-perfect harmonic trumpet (Macaluso and Dalmont, 2011). Some studies investigated  
44 the relationship between input impedance features and psycho-acoustic criteria: Poirson optimized  
45 the trumpet using objective functions based on the input impedance **and targets defined by trum-**  
46 **pet players preferences** (Poirson *et al.*, 2007). Guillauteau looked for empirical relations between  
47 playing frequencies and resonance frequencies to optimize clarinets (Guilloteau, 2015).

48 However valuable, these works focused exclusively on instrument performance, neglecting a  
49 crucial element in sound production: the musician embouchure. In particular, the studies of Eveno  
50 et al. showed that the relationship between the resonance frequencies of the impedance and the  
51 actual frequencies of the sounds played by musicians can vary significantly (Eveno *et al.*, 2014).

52 Although the impedance of an instrument provides interesting information about sound quality,  
53 prediction of “playability” and sound qualities of **brasses** based solely on impedance remains dif-  
54 ficult.

55 A second approach is based on a holistic model of the physical phenomenon, coupling the  
56 instrument and the musician embouchure, to produce sound simulations representative of the in-  
57 strument quality. Using this approach, the authors integrate sound simulations in the optimization  
58 process. These simulations are obtained from a physics-based model to account for the interaction  
59 of the instrument with a virtual musician embouchure (Tournemenne *et al.*, 2017). In a previous  
60 study, the instrument’s intonation was optimized based on simulated playing frequencies (Tourne-  
61 menne *et al.*, 2017). Two examples were considered, optimizing 2 and 5 of the bore’s geometrical  
62 parameters, respectively; results were quite encouraging.

63 The main objective of the present paper is to extend this new **optimization** paradigm in order to  
64 assess both its potential and limitation. The two main novelties of this paper are the optimization  
65 of criteria based on the instrument sounds spectra, and the inclusion of constraints in the problem  
66 formulation. Three other contributions are noticeable: i) an improved version of the optimization  
67 method has been implemented, ii) a new solver is introduced, and iii) the performance limits of the  
68 optimization method are tested by considering **10 geometrical variables of the bore**. A trumpet is  
69 used as a **representative** brass instrument to demonstrate the proposed design optimization method.

70 The paper is organized as follows. We first present extensive details on the physics-based  
71 model and the simulation technique. We then formulate the optimization problems and describe  
72 the principles of the MADS algorithm and the framework for surrogate-assisted optimization.

73 Finally, we conduct a case study concerning the shape optimization of a trumpet with ten design  
 74 variables and draw conclusions.

## 75 II. TRUMPET MODELING

76 In this study, we utilize an elementary model of a brass instrument under playing conditions:  
 77 the vibrating lips are modeled as a one-degree-of-freedom (1-DOF) outward-striking valve, non-  
 78 linearly coupled to the air column of the brass instrument. This elementary model is a good com-  
 79 promise between simplicity and efficiency. While the 1-DOF model cannot model real musician  
 80 lips exactly, (Yoshikawa, 1995) it is able to mimic a large range of playing phenomena (see for  
 81 example the pioneering work of Elliot and Bowsher (1982), (Elliott and Bowsher, 1982) or the  
 82 more recent works of Petiot et al. (2013) (Petiot and Gilbert, 2013) and Velut et al. (2017) (Velut  
 83 et al., 2017)). Similar to Chen and Weinreich (1996), (Chen and Weinreich, 1996) we argue that  
 84 while the lips may not be entirely modeled by a 1-DOF model, most characteristic behaviors of  
 85 brasses can be reproduced by an outward striking reed.  
 86 Our physics-based model of the trumpet is based on Equations (1), (2), and (3), which all depend  
 87 on three periodic variables: the opening height  $h(t)$  of the two lips, the volume flow  $u(t)$  of the air  
 88 jet through the lip channel and the pressure  $p(t)$  in the mouthpiece (cf. Figure 2).

$$\hat{p}(j\omega) = Z(j\omega)\hat{u}(j\omega) \quad (1)$$

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$$\frac{d^2h(t)}{dt^2} + \frac{2\pi f_\ell}{Q_\ell} \frac{dh(t)}{dt} + (2\pi f_\ell)^2(h(t) - h_0) = \frac{P_m - p(t)}{\mu_\ell} \quad (2)$$

90

$$u(t) = bh^+(t) \operatorname{sign}(P_m - p(t)) \sqrt{\frac{2|P_m - p(t)|}{\rho}} \quad (3)$$

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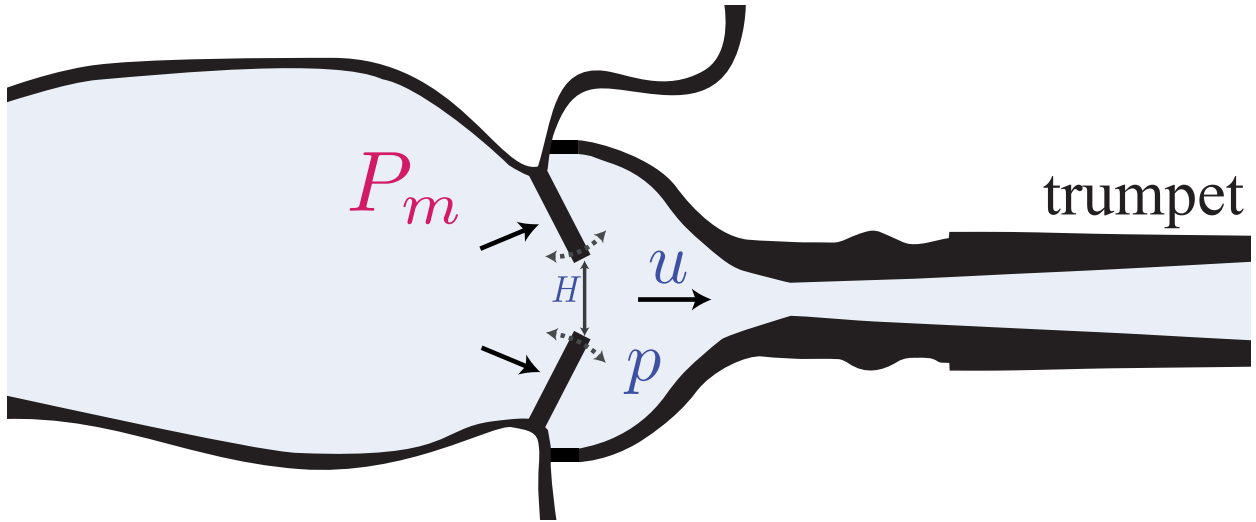


FIG. 2. Representation of the outward striking model of the lips, with the definition of the variables of the physical model:  $P_m$  (pressure in the mouth),  $h$  (lip aperture),  $u$  (volume flow),  $p$  (pressure in the mouthpiece)

(color online)

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These three equations express the acoustic impedance of the resonator, a simple harmonic oscillator for the lips model, and the coupling between the lips and the trumpet, respectively. Equation (3) shows two non-linearities: the square root originating from the Bernoulli equation, and the positive part of the lip aperture  $h^+ = \max(h, 0)$  modelling the closed lips. Several parameters are included in this model: air density  $\rho$ , input impedance  $Z$  of the trumpet, the parameters concerning musician embouchure which are  $P_m$  (the static overpressure in the mouth),  $f_\ell$  (the resonance frequency of the lips),  $\mu_\ell$  (the area density of the lips),  $b$  (the width of the lips),  $h_0$  (the rest value of the opening height of the lips) and  $Q_\ell$  (the quality factor of the resonance of the lips). Input



102 impedance  $Z$  is computed using the transfer matrix method considering plane wave propagation,  
103 visco-thermal losses (Caussé *et al.*, 1984), and a radiation function under an infinite plane baffle  
104 hypothesis.

105 It is important to assess the validity of this 1-DOF model by indicating which behaviors of  
106 brasses can be reproduced adequately with simulations and which ones cannot. Previous results  
107 using this elementary model (Petiot and Gilbert, 2013) showed that the trumpet sounds simulated  
108 are dissimilar to the real trumpet sounds played by a musician. In particular, sound spectra in per-  
109 manent regime are very different. This can be explained by inherent limitations of the model. A  
110 first limitation concerns the linear approximation of sound propagation in the brass resonator de-  
111 fined by its acoustic impedance (Equation (1)). When the instrument is played loudly and brassy,  
112 this approximation is no longer valid, and the nonlinear propagation needs to be taken into ac-  
113 count. (Myers *et al.*, 2012)

114 A second limitation concerns the lip model, which simplifies the complicated real-lips motion  
115 (Bromage *et al.*, 2010; Martin, 1942; Yoshikawa, 1995) with a 1-DOF (Equation (2)). Two-de-  
116 grees-of-freedom (2-DOF) models have been considered for time domain simulation (Adachi and  
117 Sato, 1996; Boutin *et al.*, 2015). Furthermore, measured mechanical responses of artificial (Cullen  
118 *et al.*, 2000) and real brass-players lips (Newton *et al.*, 2008) revealed that a pair of mechanical res-  
119 onances requires a 2-DOF model in order to be consistent with near threshold oscillations (Cullen  
120 *et al.*, 2000). However, although additional terms can theoretically be added to the 1-DOF model,  
121 the difficulty lies in selecting realistic values for the additional parameters (Velut *et al.*, 2017).

122 A third limitation relates to the assumption that the volume flow  $u$  (Equation (3)), which con-  
123 trols the valve effect, is proportional to the opening height  $h$  between the lips. Experimental data

124 reported in (Bromage *et al.*, 2010) for a large set of playing frequencies and sound levels showed  
 125 that the relationship may be exponential instead of linear, and dependent on the pitch and dynamic  
 126 level of the note played.

127 Nevertheless, even if nonrealistic for the spectrum of trumpet sounds, previous studies confirm  
 128 that this elementary model behaves in agreement with the main physical principles that govern the  
 129 playing of brasses (Petiot and Gilbert, 2013; Poirson *et al.*, 2005). In particular, results presented  
 130 in (Petiot and Gilbert, 2013) showed that the elementary model is able to produce differences be-  
 131 tween instruments according to playing frequency, spectral centroid, and evolution of the spectral  
 132 centroid with the playing dynamics that are, on average, in agreement with the differences noticed  
 133 when a real trumpet is playing. This results justify the use of this elementary model in an opti-  
 134 mization process for objective functions based on intonation, spectral centroid, or the evolution of  
 135 the spectral centroid.

136 Numerical solutions of this system of equations are obtained using the harmonic balance tech-  
 137 nique to simulate the sound created by a given trumpet (defined by its input impedance  $Z$ ) for a  
 138 given “virtual musician embouchure” (defined by its control parameters). The harmonic balance  
 139 technique considers the sound’s permanent regime (steady state); since the latter is periodic, the  
 140 truncated pressure is given by

$$p(t) = A_0 + \sum_{n=1}^N A_n e^{i2\pi n F t} + A_n^* e^{-i2\pi n F t}. \quad (4)$$

141 The unknowns, i.e., the amplitudes of the harmonics  $A_n$  and the playing frequency  $F$ , are deter-  
 142 mined using Newton’s method (Gilbert *et al.*, 1989).

143 To perform a sound simulation, it is necessary to define relevant values (i.e., values that lead to  
 144 a convergence towards a steady-state sound for a given note) for the parameters of the musician

145 embouchure. For a given note, experience shows that countless embouchures may lead to a steady-  
 146 state note. The choice of the range of the parameters is based both on numerical tests of the  
 147 simulations and on measurements of real trumpet players. The three variables  $P_m$ ,  $\mu_\ell$ , and  $f_\ell$  are  
 148 considered as control parameters of the simulations, and constitute the virtual embouchure. The  
 149 pressure  $P_m$  in the mouth influences mainly the dynamics of a simulated sound and ranges from  
 150 1 to 12 kPa (Fletcher and Tarnopolsky, 1999). In the following numerical experiments, we parti-  
 151 tioned this range into three parts running from 1 to 5 kPa for what we call piano ( $p$ ) dynamics, 5 to  
 152 9 kPa for mezzoforte ( $mf$ ) dynamics and 9 to 12 kPa for fortissimo ( $ff$ ) dynamics. The frequency  
 153 of the lips  $f_\ell$  enables the selection of the played regime (note): the higher the value of  $f_\ell$ , the  
 154 higher the simulated regime. Exploration tests led to a range for  $f_\ell$  that spans from 130 Hz to  
 155 480 Hz to simulate the 2<sup>nd</sup>, 3<sup>rd</sup>, 4<sup>th</sup> and 5<sup>th</sup> regime of the B $\flat$  trumpet with no valve pressed, the  
 156 regimes considered in this study. These regimes correspond to the musical notes B $\flat$ 3, F4, B $\flat$ 4,  
 157 D5–concert-pitch. Finally, in order to produce many different sounds for every regime, we add  
 158 variability to the embouchure making  $\mu_\ell$  a control parameter of the simulations, ranging from 1  
 159 to 6 kg/m<sup>2</sup> (Cullen *et al.*, 2000). In our study, the values of  $b$ ,  $Q_\ell$ , and  $h_0$  are the same for every  
 160 simulation (Cullen *et al.*, 2000).

162 The values of the control parameters considered in this study are summarized in Table I.

163 Given that above 3000Hz the impedance magnitude is flat (see Figure 1), it is not relevant  
 164 to consider many harmonics for the sound simulation. The highest studied note being D5 (587  
 165 Hz), we chose to simulate our permanent regime with only  $N = 6$  harmonics. In conclusion, for  
 166 a given trumpet (characterized by its input impedance  $Z$ ) and for a virtual musician embouchure  
 167 (characterized by the parameters  $P_m$ ,  $\mu_\ell$ ,  $f_\ell$ ,  $b$ ,  $h_0$ , and  $Q_\ell$ ), the simulation may generate one note (if

TABLE I. Values of the control parameters for the simulations considered in the study (virtual musician embouchure)

Parameter	Symbol (units)	Value
Resonance frequency of the lips	$f_\ell$ (Hz)	130 to 480
Mass per area of the lips	$\mu_\ell$ ( $kg/m^2$ )	1 to 6
Pressure in the mouth	$P_m$ (kPa)	1 to 12
Width of the lips	$b$ (mm)	10
Rest value of the opening height	$h_0$ (mm)	0.1
Quality factor of the resonance	$Q_\ell$	3

168 the system converges), corresponding to one of the regimes 2, 3, 4 and 5 of the trumpet. Each note  
 169 is characterized by its playing frequency  $F$  and the complex amplitudes of its 6 first harmonics.

170 It is important to mention that the computed sound  $p(t)$  corresponds to the sound in the mouth-  
 171 piece. According to Benade (Benade, 1966), a relevant spectrum transformation function could  
 172 be defined to compute the sound outside the instrument. The difficulty lies in the definition of  
 173 the radiated pressure, relevant from a perceptual point of view. For the optimization considered in  
 174 this work, the well-defined pressure in the mouthpiece is deemed sufficient. It is also important to  
 175 mention that the convergence of the simulation toward auto-oscillations is not ensured for a given  
 176 shape of the resonator and embouchure. The search of convenient embouchures is a complex task,  
 177 described in the following section.

### 178 III. OPTIMIZATION PROBLEM FORMULATION

179 The design optimization problem of an instrument can be formulated as the search for the  
 180 optimal geometry minimizing an objective function:

$$\min_{\mathbf{x} \in \Omega} J(\mathbf{x}), \quad (5)$$

181 where  $J : \mathbb{R}^n \rightarrow \mathbb{R}$  is the objective function, and the vector  $\mathbf{x} \in \mathbb{R}^n$  includes the design optimization  
 182 variables. The design space  $\Omega$  is a subset of  $\mathbb{R}^n$  delimited by box (bound) constraints. The design  
 183 optimization variables are the geometric parameters that define the inner shape of the bore. To  
 184 facilitate the input impedance calculations, the bore is approximated by a series of conical and  
 185 cylindrical waveguide segments. Consequently,  $\mathbf{x}$  is a vector of geometric quantities such as the  
 186 lengths and radii of cylinders or cones. The design space  $\Omega$  may be modified to obtain viable  
 187 trumpet shapes.

188 Two classes of objective functions are available considering our physics-based model and the  
 189 harmonic balance technique: descriptors based on playing frequencies and descriptors based on  
 190 sounds spectra. Many quantities based on frequency and sound spectrum can be found in the  
 191 literature; however, there is no consensus in the community regarding their influence on the instru-  
 192 ment's musical quality. These disagreements notwithstanding, this paper considers three different  
 193 objective functions based on intonation and spectral centroid given their recognized impact on the  
 194 instrument quality (Deutsch, 2013).

195 **A. Objective functions**

196 **Figure 3** describes the flowchart of the process for optimizing the shape of a trumpet bore using  
 197 physics-based sound simulations. Input impedance is computed for a design vector  $\mathbf{x}$  representing

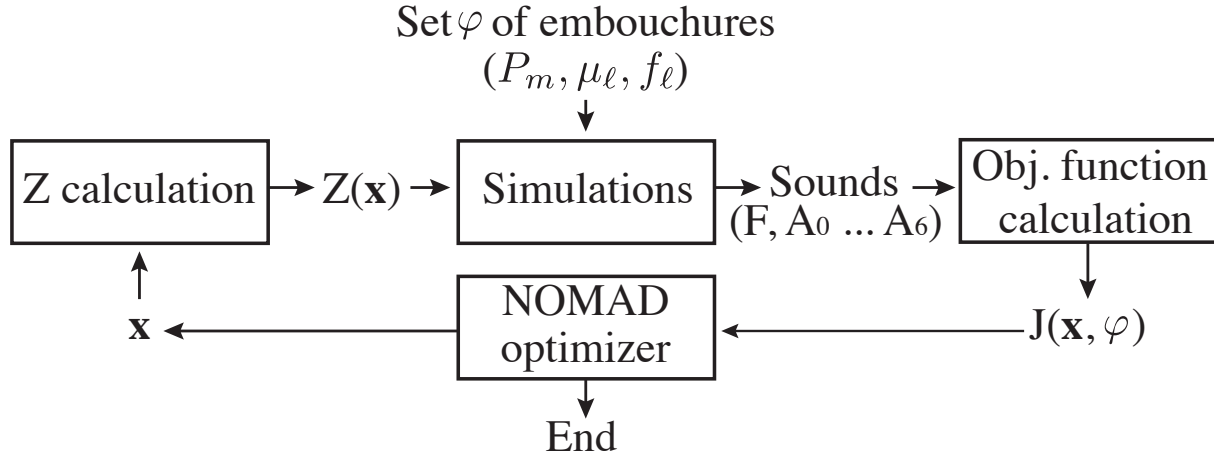


FIG. 3. Flowchart of the optimization process

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200 the resonator's geometry. This study focuses on the average behavior of the instrument across a  
 201 panel of embouchures for each note (Bb3, F4, Bb4, D5). Another approach based on ideal em-  
 202 bouchures for each note could have been adopted, which would be an interesting future line of  
 203 research. Consequently, for the  $P$  notes ( $P=4$  in this study), the harmonic balance technique simu-  
 204 lates many sounds based on the calculated input impedance  $Z(\mathbf{x})$  and a set of virtual embouchures  
 205  $\varphi_i$  for each note  $i$ . The set

$$\varphi = \bigcup_{i=1}^P \varphi_i \quad (6)$$

206 represents the entire set of embouchures used to evaluate one instrument (see [section III C](#) for  
 207 details). An objective function  $J$  is then computed using the playing frequencies  $F$  or the [harmon-](#)  
 208 [ics amplitudes](#)  $A_n$  produced by the  $\text{card}(\varphi)$  simulations ( $\text{card}(\cdot)$  denotes cardinality of a set, i.e., the

209 **number of elements in a set**). The value of the objective function (and the values of the constraint  
 210 functions introduced later) are provided to the optimization algorithm (MADS, implemented in  
 211 the NOMAD software **package** (Le Digabel, 2011)), which will propose a new design vector  $\mathbf{x}$   
 212 (see Section IV for details). The new design candidate  $\mathbf{x}$  is evaluated in the same manner, and **the**  
 213 process is iterated until the optimization algorithm termination criterion is satisfied.

### 214 1. Objective function based on intonation

215 For each note  $i$ , the average (across different embouchures) playing frequency  $\overline{F}_i(\mathbf{x}, \varphi)$  at mez-  
 216 zoforte dynamics is computed. The intonation of the note is assessed by the deviation of the actual  
 217 playing frequency, as simulated using the physics-based model, from the expected playing fre-  
 218 quency. This objective function relies on a reference note from which the ideal and actual musical  
 219 distance is computed. We chose for reference the 4<sup>th</sup> regime of the trumpet with no valve pressed  
 220 (Bb4, concert pitch), given that it is the usual tuning note of the instrument. The equal-tempered  
 221 scale is used to define the ideal distance between the studied note  $i$  and the reference note (Tourne-  
 222 [menne et al., 2017](#)).

223 For every note  $i$ , we compute the equal-tempered deviation (ETD) between the average fre-  
 224 quency of the  $i^{\text{th}}$  note  $\overline{F}(\mathbf{x}, \varphi_i)$  and the reference frequency  $\overline{F}(\mathbf{x}, \varphi_r)$  as

$$\text{ETD}_{i(\mathbf{x}, \varphi)} = \alpha_{r \rightarrow i} - 1200 \log_2 \left( \frac{\overline{F}(\mathbf{x}, \varphi_i)}{\overline{F}(\mathbf{x}, \varphi_r)} \right), \quad (7)$$

225 where  $\alpha_{r \rightarrow i}$  is the ideal difference between the reference note  $r$  and the targeted note  $i$  given by  
 226 the equal-tempered scale (-500 cents for example between Bb4 and F4). The objective function  
 227  $J_1(\mathbf{x}, \varphi)$  for the whole instrument is the average of the absolute deviation across the  $(P-1)$  notes

228 (notice that the deviation between the reference note and the 4<sup>th</sup> note is always equal to zero, given  
 229 that it is the tuning note)

$$J_1(\mathbf{x}, \varphi) = \frac{1}{P-1} \sum_{i \in \text{Notes}} |\text{ETD}_i(\mathbf{x}, \varphi)|. \quad (8)$$

## 230 2. Objective function based on the spectral centroid

231 The average spectral centroid  $\overline{\text{SC}}(\mathbf{x}, \varphi)$  at mezzoforte dynamics for every note is computed  
 232 according to the 6 harmonic amplitudes  $A_n$  of each simulated sound

$$\overline{\text{SC}}(\mathbf{x}, \varphi) = \frac{1}{\text{card}(\varphi)} \sum_{E_v \in \varphi} \text{SC}(\mathbf{x}, E_v(P_m, \mu_l, f_l)), \quad (9)$$

233 where  $E_v$  is an embouchure of the virtual musician with

$$\text{SC}(\mathbf{x}, E_v) = \frac{\sum_{n=1}^6 |n A_n(\mathbf{x}, E_v)|}{\sum_{n=1}^6 |A_n(\mathbf{x}, E_v)|}. \quad (10)$$

234 Consequently,  $\text{SC}(\mathbf{x}, E_v)$  spans from 1 to 6, representing the normalized spectral centroid. In  
 235 this work, we decided to look for the instruments having the highest spectral centroid. These  
 236 instruments would generally be considered as bright by musicians (Poirson *et al.*, 2005). This  
 237 is a somewhat arbitrary choice and other relevant descriptor/target may be found, although such  
 238 consideration is out of the scope of the paper.

239 Consequently, the objective function  $J_2(\mathbf{x}, \varphi)$  is

$$J_2(\mathbf{x}, \varphi) = \overline{\text{SC}}(\mathbf{x}, \varphi). \quad (11)$$

## 240 3. Objective function based on the spectral centroid dynamics

241 This descriptor represents the ability of the instrument to maximise the spectral centroid dif-  
 242 ference between a piano ( $p$ ) and a fortissimo ( $ff$ ) dynamics. The idea is to find the instrument



243 producing bright notes for high dynamics (high SC) while keeping a dark sound (low SC) for low  
 244 dynamics. The average spectral centroid for each note and each piano ( $\overline{SC}_p(\mathbf{x}, \varphi_i)$ ) and fortissimo  
 245 ( $\overline{SC}_{ff}(\mathbf{x}, \varphi_i)$ ) dynamics are computed. The objective function is then formulated as

$$J_3(\mathbf{x}, \varphi) = \sum_{i \in \text{Notes}} \frac{\overline{SC}_{ff}(\mathbf{x}, \varphi_i) - \overline{SC}_p(\mathbf{x}, \varphi_i)}{P} = \sum_{i \in \text{Notes}} \frac{\Delta \overline{SC}_i}{P}. \quad (12)$$

246 For this descriptor, the note D5 concert-pitch has been discarded because of the difficulty in  
 247 simulating it for low dynamics. A more application-oriented study considering the entire instru-  
 248 ment's tessitura should account for these **kind** of difficulties.

## 249 B. Optimization problems

250 In summary, we consider three different optimization problems labelled **Int**, **SC Int**, and **SC**  
 251 **Dyn**. They represent instrument design problems that are realistic from a musician point of view:

- 252 • **Int: intonation improvement:**

$$\min_{\mathbf{x} \in \Omega} J_1(\mathbf{x}) \quad (13)$$

- 253 • **SC Int: spectral centroid improvement under intonation constraint:**

$$\max_{\mathbf{x} \in \Omega} J_2(\mathbf{x}) \text{ subject to } J_1(\mathbf{x}) \leq J_{1\max} \quad (14)$$

- 254 • **SC Dyn: spectral centroid dynamics improvement:**

$$\max_{\mathbf{x} \in \Omega} J_3(\mathbf{x}) \quad (15)$$

255 **The constraint function of the SC Int problem is the objective function of the Int problem. It**  
 256 **represents the scenario where musicians are willing to trade some of their instrument's intonation**  
 257 **quality for a more brighter timbre.**

### 258 C. Finding playable embouchures

259 The main challenge lies in the simulation of many different sounds (represented by their per-  
 260 manent regimes) during the numerical evaluation of the objective function. Practically, for each  
 261 geometry  $\mathbf{x}$ , we need to find suitable virtual embouchures leading to convergence toward per-  
 262 manent regime. Furthermore, similar to an inexperienced player that would blow even the most  
 263 well-designed trumpet with a terrible sound, the virtual embouchure must be carefully selected in  
 264 order to produce realistic sounds. No analytical approach exists to deal with this challenge and  
 265 simple solutions always fall short. For example, it is not possible to define, a priori, a fixed list  
 266 of virtual embouchures that will be used for every geometry  $\mathbf{x}$ , because experience shows that the  
 267 intersection of the sets of virtual embouchures leading to convergence toward a permanent regime  
 268 for each geometry may be empty. It is far too expensive to process a complete fine grid of the 3  
 269 virtual embouchure parameters for every geometry  $\mathbf{x}$ . Consequently, a rigorous preprocessing of  
 270 the simulations is undertaken to help the simulations obtain a set of appropriate embouchures that  
 271 converge toward adequate sounds for every geometry  $\mathbf{x}$ .

272 This preprocessing is based on an exploration of the area of the design space  $\Omega$  augmented by  
 273 the 3 embouchure parameters leading to convergence of the sound simulation. If  $\mathbf{x}$  is in  $\mathbb{R}^2$ , the  
 274 space to explore has 5 dimensions: 2 geometric variables and 3 embouchure variables ( $P_m$ ,  $\mu_l$ ,  
 275  $f_l$ ). To explore this space, a five-dimensional Latin hypercube is built and the harmonic balance  
 276 technique tries to simulate every sample.

277 In order to discard the simulations of unrealistic sounds mentioned above, we use a criterion  
 278 representing the amplitude of the simulated sound relatively to the pressure in the mouth. If the

279 amplitudes of the harmonics are large enough relative to the mouth pressure  $P_m$  produced by the  
 280 virtual musician, the sound is considered appropriate

$$\frac{\sqrt{\sum_{n=1}^6 A_n^2}}{P_m} \geq \alpha. \quad (16)$$

281 Given the exploration and the criterion, an empirical method finds adequate virtual em-  
 282 bouchures for any geometry  $\mathbf{x}$  of the design space. There are two key differences between the  
 283 preprocessing presented here and that reported in (Tournemene *et al.*, 2017): i) the definition of  
 284 the criterion threshold  $\alpha$  based on live recordings and ii) a more robust technique used to define  
 285 the set of virtual embouchures  $\varphi$  for any bore, both summed up in the following paragraph.

286 The live recordings of 3 helped trumpeters playing several times the 4 notes allowed us to  
 287 estimate the standard deviation of playing frequency for each note . We then defined  $\alpha$  in order  
 288 to obtain simulations having approximately the same standard deviation of playing frequency. In  
 289 practice we defined one  $\alpha$  per note and dynamic ( $p$ ,  $mf$ ,  $ff$ ); its value ranges from 0.85 (D5) to  
 290 1.17 (Bb 3). During the optimization, the procedure defining  $\varphi$  for every bore relies on a maximal  
 291 distance from the corresponding cloud of successful embouchures found during the preprocessing,  
 292 above which a virtual embouchure is discarded. In the interest of keeping the length of this paper  
 293 reasonable, we point the interested reader to the manual accompanying the source code repository  
 294 for a detailed description of the procedure ([framagit.org/rtournem/BrassOptimUsingSounds](http://framagit.org/rtournem/BrassOptimUsingSounds)).

295 It is important to mention that for numerical reasons, the quantities  $\bar{F}(\mathbf{x}, \varphi_i)$  and  $\overline{SC}(\mathbf{x}, \varphi)$  are  
 296 average values across a finite set of embouchures  $\varphi$ , randomly chosen and selected by the prepro-  
 297 cessing. The consequence is that the objective function  $J(\mathbf{x})$  is non-deterministic, i.e., different  
 298 objective function values may be obtained for the same  $\mathbf{x}$ . In practice, a set of 1000 embouchures  
 299 are simulated per note per dynamic range in order to keep the standard deviation on the numerical

300 estimation of  $J(\mathbf{x})$  as low as possible according to the law of large numbers. This choice of 1000  
301 embouchures is validated a posteriori given the small error bars in Figure 5. Additional “blackbox”  
302 properties of the objective functions under consideration include:

- 303 • The evaluation of  $J(\mathbf{x})$  may fail due to difficulties to simulate notes (find virtual em-  
304 bouchures).
- 305 • It is not possible to reliably compute the gradient of  $J(\mathbf{x})$  because of the random selection  
306 process in the selection of the virtual embouchure.
- 307 • The evaluation of the objective function can be computationally expensive (between 3 and  
308 20 minutes depending on the processor).
- 309 • We cannot assume smoothness of the objective (or constraint) functions.

310 To address these issues, we resort to the use of derivative-free optimization algorithms and a  
311 surrogate-assisted modeling strategy.

#### 312 IV. SURROGATE-ASSISTED DERIVATIVE-FREE OPTIMIZATION

313 We use the rigorous derivative-free mesh adaptive direct search (MADS) optimization algo-  
314 rithm, which has convergence properties (Audet and Dennis, Jr., 2006) and has been implemented  
315 in the NOMAD software package (Le Digabel, 2011). Every iteration of the MADS algorithm  
316 consists of two steps: the optional search and the mandatory poll. The search step can implement  
317 any user-defined strategy to obtain promising candidates. The poll step determines candidates  
318 around the incumbent solution; it ensures the convergence of the algorithm towards a local op-  
319 timum. Our strategy in the search step is to formulate and solve a surrogate problem to obtain

320 a promising candidate, i.e., we use surrogate models of the computationally-intense simulation  
 321 procedure to evaluate the objective and constraint function values. We then evaluate the real po-  
 322 tential of this promising candidate using the physics-based simulations. In addition, when the  
 323 MADS algorithm needs to proceed to the poll step, we use the surrogate models to rank-order  
 324 the poll-generated candidates and then evaluate them opportunistically using the physics-based  
 325 simulations. In this manner, we generate a large amount of information using computationally  
 326 inexpensive surrogate models but make algorithmic decisions using the high-fidelity simulations.  
 327 More details are provided in the next sections.

#### 328 A. Mesh Adaptive Direct Search

329 At each iteration  $k$  of the MADS algorithm, the trial points must lie on a mesh  $M_k$ . The mesh  
 330 size  $\Delta_k^m$  depends on the iteration number  $k$  and gets smaller as the optimization converges.

331 During each search step, a surrogate model  $\hat{J}$  is built using previous evaluations of the objec-  
 332 tive function  $J$ . Then, a second instance of MADS is used to obtain the design that minimizes  $\hat{J}$ .  
 333 This candidate design is then projected on the mesh  $M_k$  and  $J$  is evaluated. If this candidate leads  
 334 to an improvement of the solution, the surrogate model  $\hat{J}$  is updated and the search is repeated.  
 335 Otherwise, the algorithm continues with the poll step. Two possible surrogate modeling techniques  
 336 are described in the next section.

337 During each poll step, a set of candidates  $P_k$  is generated on the mesh  $M_k$ . The distance between  
 338 the incumbent solution and the candidates  $P_k$  is controlled by the poll parameter  $\Delta_k^p$  which, as  $\Delta_k^m$ ,  
 339 gets smaller as the optimization converges. The interested reader can refer to (Audet and Dennis,  
 340 Jr., 2006) for details. As mentioned earlier, we first rank-order the points of the set  $P_k$  using the

341 surrogate model  $\hat{J}$ . The physics-based sound simulation model  $J$  is then used to evaluate the points  
342 of the set  $P_k$  using an opportunistic strategy: If a point is feasible and leads to an improvement of  
343 the objective function, the evaluation process is aborted and the algorithm iterates. Note that if a  
344 more feasible point is found during the poll step, the mesh and poll parameters are increased so  
345 that the algorithm can explore other areas of the design space. Otherwise, these parameters are  
346 reduced, which means that the iteration will operate in a closer neighborhood of the design space.

## 347 B. Surrogate Modeling Strategy

348 We consider two surrogate model approaches in this study:

- 349 • An ensemble of surrogate models approach where several surrogates of different types and  
350 with different modeling parameters are built and updated while selecting the model that fits  
351 the data best at each iteration. We use the same ensemble of surrogates as in (Audet *et al.*,  
352 2018) and (Tournemenne *et al.*, 2017): 6 polynomial regression models, 5 kernel smoothing  
353 models, and 6 radial basis function (RBF) models. The best model is chosen according to  
354 the order-error with cross-validation (OECV) metric presented in (Audet *et al.*, 2018).
- 355 • A LOcally WEighted Scatterplot Smoothing (Talgorn *et al.*, 2018) (LOWESS) surrogate  
356 model. This model consists of building a local polynomial regression around the point  $\mathbf{x}$   
357 where we wish to predict the objective function. In the construction of this local regression,  
358 data points close to  $\mathbf{x}$  are given more importance than those further away from  $\mathbf{x}$ .

## 359 V. APPLICATION

360 We consider three problem with ten design optimization variables: **Int**, **SC Int** and **SC Dyn**.

361 We have also considered these problems with two design variables similarly to (Tournemenne  
362 *et al.*, 2017), but we ommit them to keep the paper length reasonable. Since it can be useful to  
363 optimization novices, we have made it available online at this [link](#).

364 The initial bore  $\mathbf{x}_0$  is close to an existing trumpet bore (whose internal diameter has been mea-  
365 sured with different balls of decreasing diameter inserted in the trumpet, and a gauge to measure  
366 their position inside the instrument).

367 The design problems are solved with a budget of 200 function (or blackbox) evaluations. This  
368 maximum number of function evaluations is defined empirically by observing the evolution of the  
369 objective functions in order to minimize computational cost (i.e., avoid unnecessary evaluations  
370 that do not improve the function value significantly, see Figure 4). Moreover, to ensure a reli-  
371 able quantification of the efficiency of the optimization method, each problem is solved 10 times  
372 (with different starting points) for each of the 2 surrogate modeling approaches (using either an  
373 ensemble of surrogates according to (Audet *et al.*, 2018) or locally weighted regression models  
374 according to (Talgorn *et al.*, 2018)). Given that 3 design problems are studied, there is a total of  
375 60 optimization jobs (3 problems  $\times$  2 surrogate approaches  $\times$  10 starting points).

376 In order to undertake this considerable computational endeavor, we relied on a high perfor-  
377 mance computing cluster, parallelizing the sound simulations on 2 Haswell Intel® Xeon® E5-  
378 2680 v3 2.5 GHz processors providing 24 cores for each of the 60 jobs. One evaluation of the  
379 objective function took between 2min 40sec and 3min 50sec for **Int** and **SC Int** (4000 sounds

380 simulated), depending on the difficulty to simulate sounds for the considered geometry  $\mathbf{x}$ . We pro-  
 381 vide sounds of the studied notes of the initial trumpet as supplementary materials<sup>1</sup>. These sounds  
 382 are made of the first 6 harmonics of the permanent regime (no transients).

### 383 A. Design Optimization Problem with 10 Variables (10d problem)

384 The ten design variables represent the geometry of the leadpipe which is an important part of  
 385 the bore that connects the mouthpiece to the tuning slide. The leadpipe, roughly conical, has a  
 386 significant influence on the intonation and timbre of the instrument (Petiot and Gilbert, 2013).  
 387 Eleven parts of equal length ( $l=20\text{mm}$ ) are considered. The design variables are the inner radii of  
 388 the leadpipe at the connection between two parts (10 variables out of 12 control points because  
 389 the initial and last control points are fixed at 4.64 and 5.83 mm, respectively). These 10 inner radii  
 390 values span from 4.5 to 6 mm. The rest of the instrument corresponds approximately to a standard  
 391 trumpet.

392 In this realistic design space, the high dimensionality requires efficient optimization: a dis-  
 393 cretization of the space with a granularity of 0.5 mm (20% of the range of each dimension) would  
 394 necessitate  $4^{10}$  function evaluations (more than 1 million, which is not tractable in a reasonable  
 395 computation time).

396 Figure 4 presents the performance of the optimization approaches for the three 10-d problem  
 397 formulations. The initial value for  $J_1$  is 8.7 cents. The initial value for  $J_2$  and  $J_3$  are 2.23 and 0.04  
 398 (value of SC), respectively, as can be seen in Figure 5.

400 On average, the LOWESS surrogate approach yields slightly better designs for  $J_1(\mathbf{x}, \varphi)$  and  
 401 better results for  $J_3(\mathbf{x}, \varphi)$ . For Int ( $J_1$ ) the best objective function value obtained is 0.1 cents,



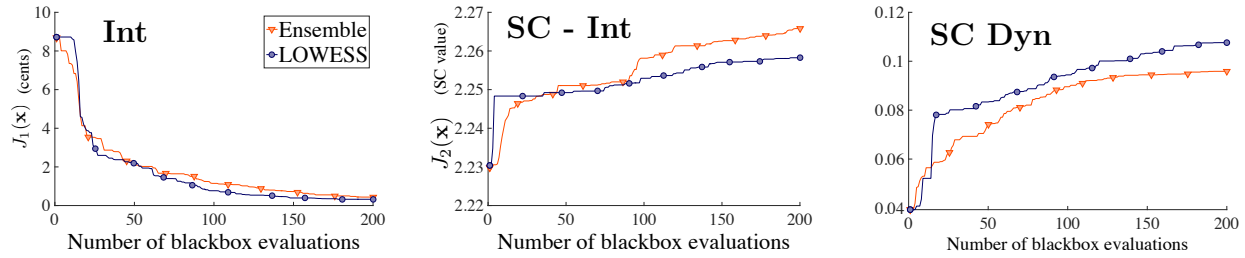


FIG. 4. Evolution of the objective function values for the 3 10-d problem formulations; from left to right:

**Int**, **SC Int**, and **SC Dyn** (color online)

402 and the best intonation improvement is 8.6 cents. This represents a 99% improvement. For **SC -**  
 403 **Int** ( $J_2$ ) the best objective function value obtained is 2.27 (value of SC), and the average spectral  
 404 centroid improvement is 0.04. This represents a 1.8% overall improvement  $((2.27 - 2.23) / 2.23)$ .  
 405 For **SC Dyn** ( $J_3$ ) the best objective function value obtained is 0.14 (value of SC), and the spectral  
 406 centroid difference improvement is 0.1. This optimal bore improves 35 times the  $J_3$  performance  
 407 of the initial bore (0.14 / 0.04). Yet, measurements on an expert trumpet player playing Bb4 concert  
 408 pitch show a SC increase around 0.8 between a  $p$  and  $ff$  note for the 6 first harmonics, which is  
 409 more than 5 times superior to the simulated values of the optimum. These results are in accordance  
 410 with (Petiot and Gilbert, 2013). Even if the method optimizes the spectral centroid variation, the  
 411 model does not allow the prediction of realistic spectral centroid values. Non-linear propagation  
 412 in the bore should be taken into account.

413 Figure 5 provides a finer acoustical analysis of these results showing the contributions of each  
 414 note to the objective functions for the initial bore and the optimal bore. The error bars are computed  
 415 following the guidelines of the Joint Committee for Guides in Metrology (JCGM, 2008). For **Int**,  
 416 the Bb3 and F4 show significant improvements of 7.5 and 13.6 cent, respectively, which are supe-

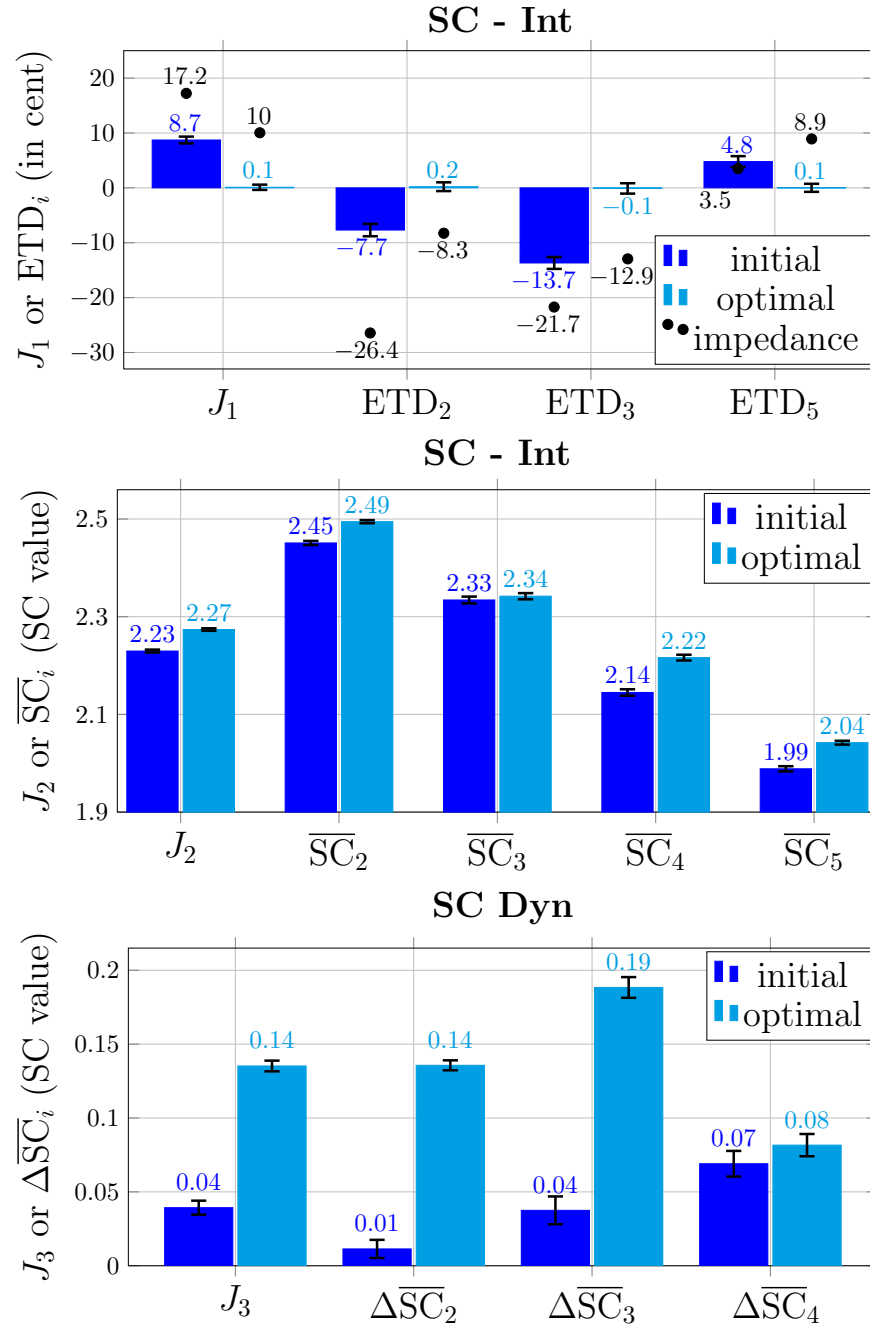


FIG. 5. On the top part, the columns represent from left to right  $J_1$  value and the non zero ETDs. Two bores are evaluated, the initial bore of all the optimization jobs and the best bore from the most successful job (out of the 20 available). The error bars equal to 2 standard deviations of the estimated quantity. Equivalent plots for the design problems **SC - Int** and **SC Dyn** are drawn below.  $\overline{SC}_i$  is  $\overline{SC}$  restricted to  $\varphi_i$ . In addition, the values of  $J_1$  and the corresponding ETDs, obtained with the input impedance peaks frequency values, are presented in black dots.

rior to the classical just-noticeable difference (JND) of 5 cents. Bb4 being the relative reference, it is always considered perfectly in tune. Since the initial value of D5 is already low (4.8 cent) the improvement of 4.7 cent is slightly lower than the JND. The sound simulation results concerning intonation are in agreement with the impedance peaks frequency values except for D5, for which the optimal trumpet seems less in tune when considering the impedance peaks frequency values. For **SC - Int**, the highest improvement is 0.08 (value of SC) for Bb4 which is at the same level than the JND of 0.1 reported in (Jeong and Fricke, 1998). Consequently, for Bb3, F4 and D5, the improvements seem negligible, rising to 0.04, 0.01 (error bars level), and 0.5, respectively. For **SC Dyn**, the improvements for Bb3 and F4 are above the JND (0.13 and 0.15, respectively), contrary to Bb4 (0.01).

Figure 6 shows the leadpipes yielding the best value for each design problem.

As in (Tournemenne *et al.*, 2017), the optima are counter intuitive since the leadpipe does not have a positive slope along the whole trumpet axis. This kind of shape for a leadpipe is not common among trumpets because it is very difficult to manufacture. The optimization algorithm was able to explore the design space in order to find unusual designs. Finally, the geometrical differences between the 3 optima and the initial leadpipe are on the order of the millimeter for several control radii, which will lead to noticeably different instruments when manufactured.

## B. Discussion

Concerning intonation, the objective function value based on sound simulations is always below the one obtained only with the input impedance peaks (cf. black dots of Figure 5). This has been verified on more examples (Tournemenne, 2017), and would mean that the musician always plays

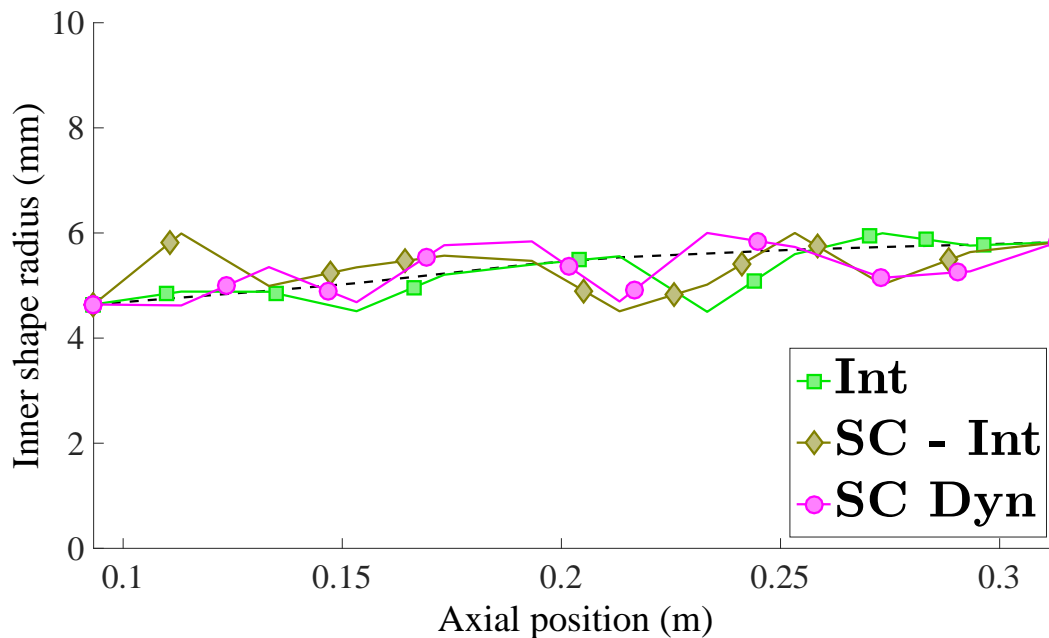


FIG. 6. Representation of the leadpipe inner radius along the instrument axis; the black dotted line to the initial geometry (measured on our trumpet); each other line corresponds to the best design found by each objective over 20 jobs (color online)

438 more in tune that would suggest the resonance frequency values of the input impedance. This is  
 439 necessarily an effect of the non-linear part of the model which requires further study. The history  
 440 plot of the **Int** design problem demonstrates a significant intonation improvement, above JND:  
 441 the objective function is decreased by 99% to 0.1 cents. Such a level of performance has been  
 442 achieved for a small price (200 evaluations compared with the million evaluations needed by brute  
 443 force). Future studies may consider even more design variables. Concerning the spectral centroid,  
 444 the results show improvements of the objective function  $J_2$  and  $J_3$ , even if they remain limited  
 445 and close to the JND. More marked improvements would certainly occur on real trumpets when  
 446 played.

447 Regarding the surrogate modeling approach, it is hard to tell whether one is consistently better  
448 than the other **as they seem** to exhibit the same exploration to exploitation ratio of the design  
449 space. It should be noted that the locally weighted regression models take longer to compute than  
450 the ensemble of surrogates in high-dimensional problems **(in our case, the difference is one hour**  
451 **vs. few minutes for ten variables)**.

## 452 VI. CONCLUSIONS

453 **In this paper, we extended a new paradigm for design optimization of brass instruments. This**  
454 **new paradigm goes beyond impedance based optimization.**(Braden *et al.*, 2009; Guilloteau, 2015;  
455 Kausel, 2001; Macaluso and Dalmont, 2011; Noreland *et al.*, 2013, 2010; Poirson *et al.*, 2007).  
456 **We consider the optimization of objective functions (possibly subject to constraints) based directly**  
457 **on the sounds spectrum, which, to the best of our knowledge, is a novel approach. The original-**  
458 **ity of the approach lies in the fact that the objective function is not limited to a characterization**  
459 **of the instrument alone, but includes virtual musicians in an physical model, to optimize directly**  
460 **the instrument sounds. The main contribution of this paper is to demonstrate how physics-based**  
461 **sound simulations can be integrated in an iterative optimization algorithm, which requires that**  
462 **simulations converge automatically toward auto-oscillations for every considered bore of the de-**  
463 **sign space, without any assistance of the user. A second contribution concerns the optimization**  
464 **of objective functions based on a particular dimension of the timbre of the sounds, the spectral**  
465 **centroid. Applied to the optimization of a trumpet, the results show that the optimization method,**  
466 **based on the MADS algorithm, is efficient to define optimal solutions in a reasonable computation**  
467 **time, with or without constraints, for problems up to 10 design variables.**

468 While the approach shows promising potential, there is room for improvement. Even if it is ef-  
469 ficient to reproduce differences between instruments concerning intonation and spectral centroid,  
470 the elementary model could be improved to generate a more realistic sound spectrum. The sound  
471 optimized in this work is the sound in the mouthpiece. Even if this does not change the principle  
472 of the method presented, it could be interesting to define a relevant radiated pressure outside the  
473 instrument, and to include it in the optimization considerations. Another valuable contribution to  
474 this numerical study concerns the manufacturing of the optimal instruments and their objective  
475 and subjective study. This would help evaluate actual improvement. Regarding implementation,  
476 the influence of the selection process of the virtual embouchure could be investigated further, as it  
477 may provide more robust descriptors of the ease of playing of the considered instruments. Regard-  
478 ing the methodology, a study of temporal sound simulations could lead to new classes of objective  
479 functions, such as attack times. More ambitious still, the inclusion of non-linear propagation in  
480 simulations would produce more realistic sounds improving the objective functions considered  
481 in this work. Finally, the main challenge in the design of musical instrument lies in the defini-  
482 tion of judicious objective functions providing actual insight of the instrument intrinsic quality.  
483 This task may be accomplished by working side-by-side with instrument makers whose empirical  
484 understanding may be translated to computational principles and models.

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491 <sup>1</sup>See Supplementary materials at [URL will be inserted by AIP] for the sounds.

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