

MAY 16 2016

Geometrical parameter combinations that correlate with early interaural cross-correlation coefficients in a performance hall ✓

L. Y. Cheung; S. K. Tang



J. Acoust. Soc. Am. 139, 2741–2753 (2016)

<https://doi.org/10.1121/1.4948995>

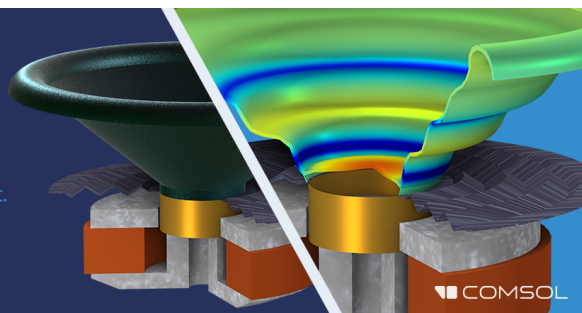


CrossMark

Take the Lead in Acoustics

The ability to account for coupled physics phenomena lets you predict, optimize, and virtually test a design under real-world conditions – even before a first prototype is built.

» Learn more about COMSOL Multiphysics®



COMSOL

Geometrical parameter combinations that correlate with early interaural cross-correlation coefficients in a performance hall

L. Y. Cheung and S. K. Tang^{a)}

Department of Building Services Engineering, The Hong Kong Polytechnic University, Hong Kong, China

(Received 22 April 2016; accepted 27 April 2016; published online 16 May 2016)

The previous binaural data of the authors measured inside two multi-purpose performance halls are re-analyzed using regression in this study. It is done in an attempt to establish a framework that can improve the prediction of early interaural cross-correlation coefficients (IACCs), but with as little measurement effort and parameters as possible. The results show that regression models consist of linear combinations of polynomials of geometrical parameters, when used together with the measurement schemes suggested previously by the authors, are sufficient for predicting the IACCs to within engineering tolerance. The predictions are better than those obtained previously by the neural network approach of the authors. The relative importance of the geometrical parameters in the prediction of IACCs is also investigated. © 2016 Acoustical Society of America.

[<http://dx.doi.org/10.1121/1.4948995>]

[NX]

Pages: 2741–2753

I. INTRODUCTION

Performance halls are essential facilities in a developed city as they are important venues for conducting leisure and cultural activities for the well-being of citizens. Their indoor environmental quality, especially the acoustics, is directly affecting the capacity of these halls to deliver their functions. There have been a lot of research efforts in the past few decades regarding the acoustical performances of performance halls, for instance Beranek¹ and Barron.² There are also surveys that investigate the audience's subjective feelings toward the hall acoustics.^{3–5} The effects of the balconies and seats on the acoustics have also been studied.^{6,7}

Studies focused on the development of psycho-acoustical indices that can quantify hall performance have been rigorously conducted in the past few decades. Apart from the commonly used reverberation time and early decay time, the energy-based indices clarity and definition have been proposed to cater for a balance between clarity and reverberation.^{8,9} Ando and Imamura¹⁰ and Barron and Marshall¹¹ found that the interaural cross-correlation coefficients (IACCs) have good relationships with the perceived spatial impression, while Hidaka *et al.*¹² suggested to use them as a measure of acoustical quality. There are also studies investigating the relationships between various developed indices, for instance, Okano *et al.*,¹³ Carvalho,¹⁴ and Tang.¹⁵

The prediction of objective performance indices is also a hot topic. However, owing to the complexity of a performance hall, analytical formulas are hardly available. There are formulas for the prediction of energy-based indices, but it is done with an assumption of exponential sound decay in the halls.^{16,17} The ray-tracing algorithm¹⁸ follows the development of rays and is able to provide information for the estimation of basically all performance hall indices when used together with the image-source method. However, the modeling of surfaces and the complex internal hall geometry

have been a big challenge. Nannariello and Frickle¹⁹ investigated the application of neural networks for predictions. However, the neural network requires a reliable database to function. Thus, general information from different halls may only be able to give indicative predictions. Cheung and Tang²⁰ recently conducted detailed surveys inside two multi-purpose performance halls in Hong Kong. They have also investigated the effectiveness of neural network predictions inside these halls by using a limited number of binaural measurements to form the database. While the predictions of energy-based indices are acceptable, the mean square errors of $IACC_{0.80}$ ($IACC_E$) can be more than 30% of the mean measured values. The situation with sound canopy is better.

In this study, the binaural measurements of Cheung and Tang²⁰ are re-analyzed using the regression approach in an attempt to find out an improved scheme for the prediction of the mid-frequency early $IACC_{E3}$ using a small number of measured data and regression inputs. The binaural quality index ($1 - IACC_{E3}$) relates closely with the mid-frequency hall spaciousness.^{19,21} In the foregoing discussions, a detailed regression analysis done using data obtained from one of the halls surveyed by the authors previously is presented in the first place. It is followed by a validation using the results of the other hall studied by the authors.²⁰

II. THE SURVEYED HALL AND MEASUREMENT

Hall A of Cheung and Tang²⁰ is chosen for the illustration of the present regression analysis approach. It is of the rectangular internal shape with a total seating capacity of 1372 (stall, 589; upper stall, 443; balcony, 340). Figure 1 illustrates the layout and dimensions of this hall. It is a multi-purpose hall with two basic settings: proscenium and concert (Fig. 2). This design is typical in the Hong Kong practice.

Binaural measurements were carried out extensively inside this hall using the DIRAC system operated in the maximum length sequence mode²² and the Brüel and Kjær 4100

^{a)}Electronic mail: shiu-keung.tang@polyu.edu.hk

Head and Torso Simulator (HATS) in the previous study of the authors.²⁰ A Brüel and Kjær 4296 omni-directional source located on the centerline of the stage 1 m inward from the stage edge was used as the sound source. Height of the source was 1.6 m from the stage floor. One hundred and eighty-two measurement points were involved (stall, 73; upper stall, 56; balcony, 53). They were essentially uniformly distributed within different sub-areas of the hall and accounted for $\sim 13\%$ of the total seating capacity. Though the percentage audience coverage in the measurement is not large, this number is already very large compared to those in many hall studies (for instance, San Martin and Arana,¹⁸ Ryu and Jeon,²³ and Hidaka *et al.*²⁴). The general acoustical properties of the hall are presented in Cheung and Tang²⁰ and, thus, are not presented here. The impulse-to-noise ratios are, in general over 30 dB in the mid-frequency range.

The IACCs are estimated using the correlations between binaural signals. The geometrical parameters that can affect the correlations are believed to be the azimuthal angle ϕ , the elevation angle θ , the source-to-receiver distance D , and the path difference δ . Figure 3 gives the definitions of these geometrical parameters graphically. The azimuthal angle and elevation angle represent the angular position of a location with respect to the hall centerline and the horizontal plane, respectively. The distance D affects the strengths of the signals, while δ denotes the difference in the distances traveled by the signals before reaching the two artificial ears of the HATS. As it is targeted to study the prediction of early IACCs, only the first reflection will be considered here for the calculation of δ for simplicity, though there can be many reflections reaching the HATS within the first 80 ms. One of the signals reaching the HATS is, thus, the direct sound,

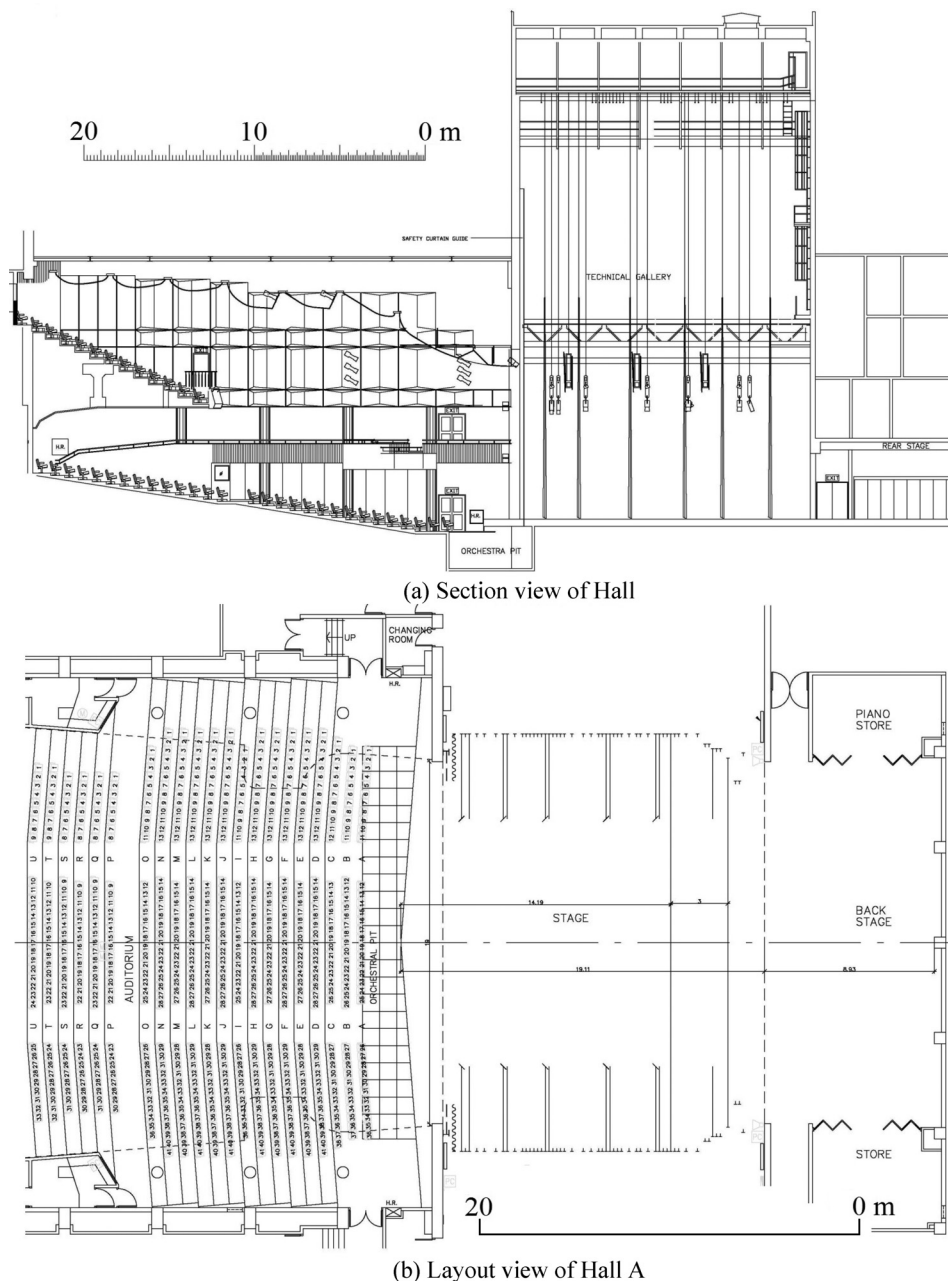


FIG. 1. Hall layout and dimensions of hall A. (a) Section view; (b) hall horizontal layout.



(a) Proscenium Stage



(b) Concert Setting (with Acoustic shells on stage)

FIG. 2. (Color online) Two different settings of hall A. (a) Proscenium stage; (b) concert setting.

while the other has undergone one reflection at the vertical hall boundary opposite to the direct sound arrival direction. It should be noted that while the first three parameters D , ϕ , and θ are independent, δ carries, implicitly, the information of D , ϕ , and θ and the hall architectural design.

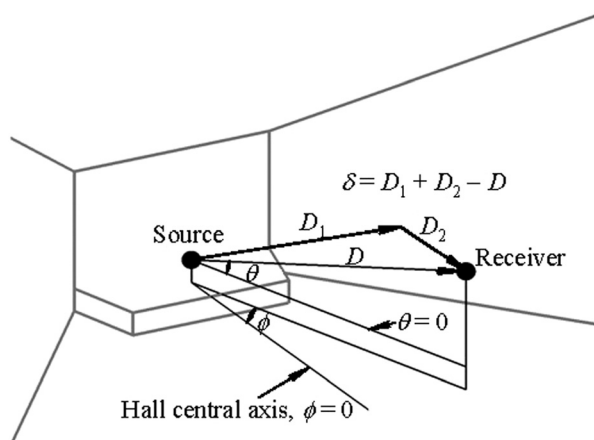


FIG. 3. Definitions of the geometrical parameters.

These regression parameters are normalized so that the coefficients are non-dimensional. The overall longitudinal length of the hall, L_{\max} , is used to normalize D , while δ is made non-dimensional using D . The angular parameters θ and ϕ are normalized by 30° and 90° , respectively. The abovementioned normalization of D , θ , and ϕ does not affect the regression statistics. However, normalizing δ by a spatially varying D rather than a constant does result in slightly better results (not shown here). The four geometrical parameters presented hereinafter are normalized quantities.

III. REGRESSION ANALYSES

Multi-variant regression analysis does not usually give rise to physically sound formulas for prediction purposes. However, it is quite commonly done for topics where analytical solution is nearly impossible to establish.^{25,26} Linear regression is not expected here as one can observe from Fig. 4 where the variations of $IACC_{E3}$ with D in the present hall are definitely non-linear. With a proscenium stage, the correlation of measured $IACC_{E3}$ with a quadratic formula of D is slightly better than the linear fit, as shown in Fig. 4(a). The cubic fit is very close to the quadratic one and, thus, the former is not presented in Fig. 4(a). Under concert hall settings, the three fittings are all weakly correlated with measurements and they give very similar standard errors (not shown here).

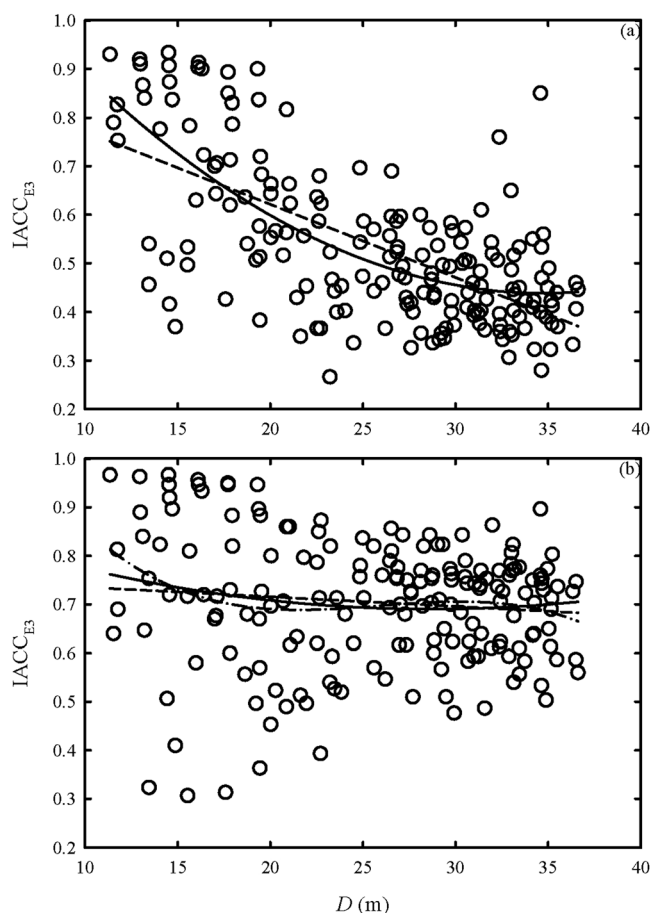


FIG. 4. Variation of $IACC_{E3}$ with distance from source D in hall A. (a) Proscenium stage; (b) concert setting. \circ , measured data; —, linear fit; - - -, quadratic fit; - · - ·, cubic fit.

Although the $IACC_{E3}$ is not a sole function of D , Fig. 4 illustrates that it tends to decrease with increasing D , though the trend under the more reverberant concert hall is weak.

As there are two hall settings and each of them results in different acoustical properties of the hall, the corresponding results are analyzed separately. There are many non-linear functional forms for curve fitting, but the polynomial one is adopted here for simplicity as well as practicality. Cross terms formed by the products of the different geometrical parameters are not considered.

A procedure is developed to generate the regression models in this study systematically. One major objective here is to keep as little regression inputs as possible. First, a quadratic form of D is adopted as hinted by Fig. 4 (discussed further in Sec. III C). Then, the most effective parameter among ϕ , θ , and δ is included with the order of the corresponding polynomial increased until a drop of prediction efficiency (reflected by a higher standard error or lower adjusted R^2) is observed. The next effective parameter is then added to the model and this cycle continues until all the four geometrical parameters are tested. This procedure should guarantee that a regression model of the lowest possible standard error is generated.

A. Proscenium stage setting

Proscenium stage is usually adopted for conducting musicals or when the hall is used as an auditorium. This hall is marginally symmetrical in term of acoustical properties.²⁰ Table I summarizes the regression statistics of various combinations of geometrical parameters with $IACC_{E3}$. All 182 measurement data sets are included. This is referred to, hereinafter, as measurement scheme A. The analysis is started with the quadratic form of D . The regression results with $|\phi|$ are significantly better than those with ϕ (not shown here) and, thus, only those with the former are presented. This is

probably due to the acoustical symmetry of the hall under the proscenium setting as shown in Cheung and Tang,²⁰ although marginal. One can observe that ϕ is more influential than θ and δ .

Since all the 182 measurement data sets are used in the regression analysis, the number of inputs is large. The better performance of model PA08 than model PA09 shows that the implicit inclusion of θ in δ is not as effective as the direct inclusion of θ once ϕ is included in the regression model. This indicates that δ is the least important parameter among the four geometrical parameters studied in the present investigation. It can be used to fine-tune the regression model performance provided that the number of data sets available for the analysis is large enough. The best performing model is PA14, which consists of a linear combination of a sixth-order polynomial of θ and a third-order polynomial of $|\phi|$, but no δ . In fact, the standard errors of models PA05–PA18 are all less the root-mean-square differences by the neural network prediction schemes of Cheung and Tang.²⁰ However, it is not effective to predict the $IACC_{E3}$ distribution in a hall using measurement data covering $\sim 13\%$ of the audience seats. It is done here to give roughly an idea on the best one can achieve by regression analysis. Model PA18 is not generated using the present proposed procedure, but is included here for later discussion.

There can be many ways to select measurement points, but those of Cheung and Tang²⁰ appear to be very logical choices. However, the one with only nine points is not suitable as such a measurement scheme will result in extrapolation of regression formula during prediction, which will certainly give rise to large errors. In the rest of Sec. III, the performances of the other three measurement schemes adopted by Cheung and Tang²⁰ are investigated. Figure 5 shows these schemes, namely, schemes B, C, and D. Scheme B includes 18 measurement points on the near and far boundaries of each sub-area in the hall. Scheme C includes 27

TABLE I. Regression analysis at 95% confidence level for the proscenium stage case of hall A with all 182 data sets included (scheme A).

Model	Regression inputs ^a	Correlation coefficient, R^2	Adjusted R^2	Standard error, ε	F	F_{critical}	Significance
PA01	D, D^2	0.4575	0.4515	0.1213	75.47	3.05	0.000
PA02	$D, D^2, \phi $	0.7297	0.7251	0.0859	106.18	2.66	0.000
PA03	D, D^2, θ	0.4730	0.4641	0.1199	53.26	2.66	0.000
PA04	D, D^2, δ	0.6148	0.6083	0.1025	94.71	2.66	0.000
PA05	$D, D^2, \phi , \phi ^2$	0.7336	0.7276	0.0855	121.84	2.42	0.000
PA06	$D, D^2, P(\phi , 3)$	0.7383	0.7309	0.0850	99.32	2.27	0.000
PA07	$D, D^2, P(\phi , 4)$	0.7389	0.7299	0.0851	82.52	2.15	0.000
PA08	$D, D^2, P(\phi , 3), \theta$	0.7657	0.7576	0.0806	92.30	2.15	0.000
PA09	$D, D^2, P(\phi , 3), \delta$	0.7434	0.7346	0.0843	84.49	2.15	0.000
PA10	$D, D^2, P(\phi , 3), P(\theta, 2)$	0.7903	0.7818	0.0765	93.66	2.06	0.000
PA11	$D, D^2, P(\phi , 3), P(\theta, 3)$	0.7959	0.7865	0.0757	84.34	1.99	0.000
PA12	$D, D^2, P(\phi , 3), P(\theta, 4)$	0.8116	0.8017	0.0729	82.30	1.93	0.000
PA13	$D, D^2, P(\phi , 3), P(\theta, 5)$	0.8183	0.8077	0.0718	77.01	1.89	0.000
PA14	$D, D^2, P(\phi , 3), P(\theta, 6)$	0.8208	0.8092	0.0715	70.80	1.85	0.000
PA15	$D, D^2, P(\phi , 3), P(\theta, 7)$	0.8216	0.8089	0.0716	64.85	1.81	0.000
PA16	$D, D^2, P(\phi , 3), P(\theta, 6), \delta$	0.8210	0.8083	0.0717	64.58	1.81	0.000
PA17	$D, D^2, P(\phi , 3), P(\theta, 6), P(\delta, 2)$	0.8210	0.8072	0.0719	59.28	1.78	0.000
PA18	$D, D^2, \phi , P(\theta, 2)$	0.7857	0.7796	0.0769	129.02	2.27	0.000

^a $P(x, n)$, polynomial in x of order n .

measurement points, which are made up of the 18 measurement points in scheme B and additional points in the middle of each sub-area. Scheme D, which includes 45 measurement points, is formed by adding two rows of measurement points on the two sides of the middle longitudinal row of measurement points in scheme C.

Table II summarizes the regression statistics under scheme B. With only 18 data sets, the number of plausible regression models is very much reduced and the standard errors are considerably larger than those in Table I. Though model PB04 consists of only D and δ , it still gives a satisfactory performance (though marginal) as δ carries the information of ϕ and θ . However, this parameter is not useful once both θ and $|\phi|$ are included in the regression model. Under a small number of data sets that tend to restrict the number of inputs to a regression model, models PB07 and PB09, which do not involve δ , are the best two for the prediction of $IACC_{E3}$. The latter is only slight better than the former. The corresponding standard errors are less than or comparable to those root-mean-square differences presented in Cheung and Tang.²⁰

The results obtained under scheme C do not differ much from those under scheme B, although the number of data sets is increased from 18 to 27 (Table III). Model PC09, which consists of the same inputs as model PB09, gives the best prediction performance. Model PC07 is the second best. The standard errors are slightly reduced. Whereas 45 data sets are included in scheme D, the number of plausible regression models remains unchanged as shown in Table IV. Again, the implications from Table IV are very similar to those from Tables II and III. Model PD09, which is the counterpart of models PB09 and PC09, performs the best. Therefore, one can conclude that when the number of data sets available for regression modeling is small, a regression model made up of a linear combination of a constant, a quadratic polynomial in D , a linear term with $|\phi|$, and a quadratic polynomial in θ is the best for the prediction of $IACC_{E3}$ in the surveyed hall A under the proscenium stage setting.

The standard errors presented in Tables I–IV show the errors of the regression model prediction with reference to the data set in each scheme. In order to understand further the effectiveness of using these models to prediction the $IACC_{E3}$ distribution in the hall, the $IACC_{E3}$ of the 182 measurement points in scheme A are predicted by models PA14, PA18, PB09, PC09, and PD09. Model PA18 is counterpart of models PB09, PC09, and PD09 in scheme A. It is included here for the sake of comparison.

Figures 6(a) and 6(b) illustrate, in the form of box plots, the corresponding distributions of the regression residues, Δ , that is, the prediction errors at the abovementioned 182 locations and those of $|\Delta|$, respectively. As shown in Fig. 6(a), the distributions of Δ are symmetrical and the mean of Δ is close to zero. However, it is more practical to analyze the distributions of $|\Delta|$ as it is always the absolute deviation that is more of a concern. It can be observed from Fig. 6(b) that the performances of models PA18 and PD09 are very similar. In fact, model PD09 gives a slightly lower $|\Delta|$ median than model PA18. The numbers on the left-hand-side

ordinate of Fig. 6(b) show the standard deviation of Δ , which is also the root-mean-square deviation between predictions and measurements. All these regression models appear to outperform the earlier neural network simulations of the authors.²⁰ The residue distributions show that scheme C can be a good choice for a tradeoff between prediction accuracy and manpower of measurement. It should also be noted that although the models PA18, PB09, PC09, and PD09 are obtained from different measurement schemes, they have the same inputs and the coefficients inside the models are reasonably close to each other (Table V). They are basically the same model. The models in Table V that begin with a “C” are for the concert setting and will be discussed in Sec. III B. One should note that the coefficients in the regression formulas are only valid for hall A. They are expected to vary from hall to hall.

B. Concert hall setting

The acoustic shell covers the rear side, the ceiling, and the two vertical sides of the stage linking to the back stage [Fig. 2(b)]. It is used during the conduction of concerts and singing contests. However, the hall is not so acoustically symmetrical in the presence of this shell.²⁰ Following the procedure adopted in the analysis of the proscenium stage setting results, the plausible regression models for predicting $IACC_{E3}$ under the concert setting are developed.

The acoustically non-symmetrical hall implies $|\phi|$ should not be included in the regression analysis. The results obtained using measurement scheme A are tabulated in Table VI. The best performing regression model is CA22, which consists of high order polynomials in ϕ and δ . However, the inclusion of δ only slightly improves the standard error. It is, again, only important when ϕ is not included in the regression modeling. Actually, the standard error is not improved significantly after model CA11. Compared to the results obtained with the proscenium stage, the higher order of the ϕ polynomial within the regression model under the concert setting tends to imply that the $IACC_{E3}$ is more correlated with ϕ when the hall is in the concert operation mode. The multiple reflections by the acoustic cells within the stage give rise to stronger sound radiation and more organized radiation directivity. A small misalignment of the cell assembly with the stage axis will result in asymmetrical sound field inside the hall.

With very few measurement data sets in scheme B, the regression model is only meaningful after ϕ^2 is included as shown in Table VII. Model CB11 gives the best prediction, while δ is not useful as a prediction parameter. The number of inputs to the regression models is limited as the number of available data sets is so much reduced. Similar observations can be made from Table VIII, which illustrates the regression statistics obtained under scheme C, except that δ is only marginally satisfactory to be considered as an input when ϕ is not included. The best performing model is CC11, which is basically the counterpart of model CB11. However, it will be shown later than the coefficients within these two models are quite different. They are not the same.

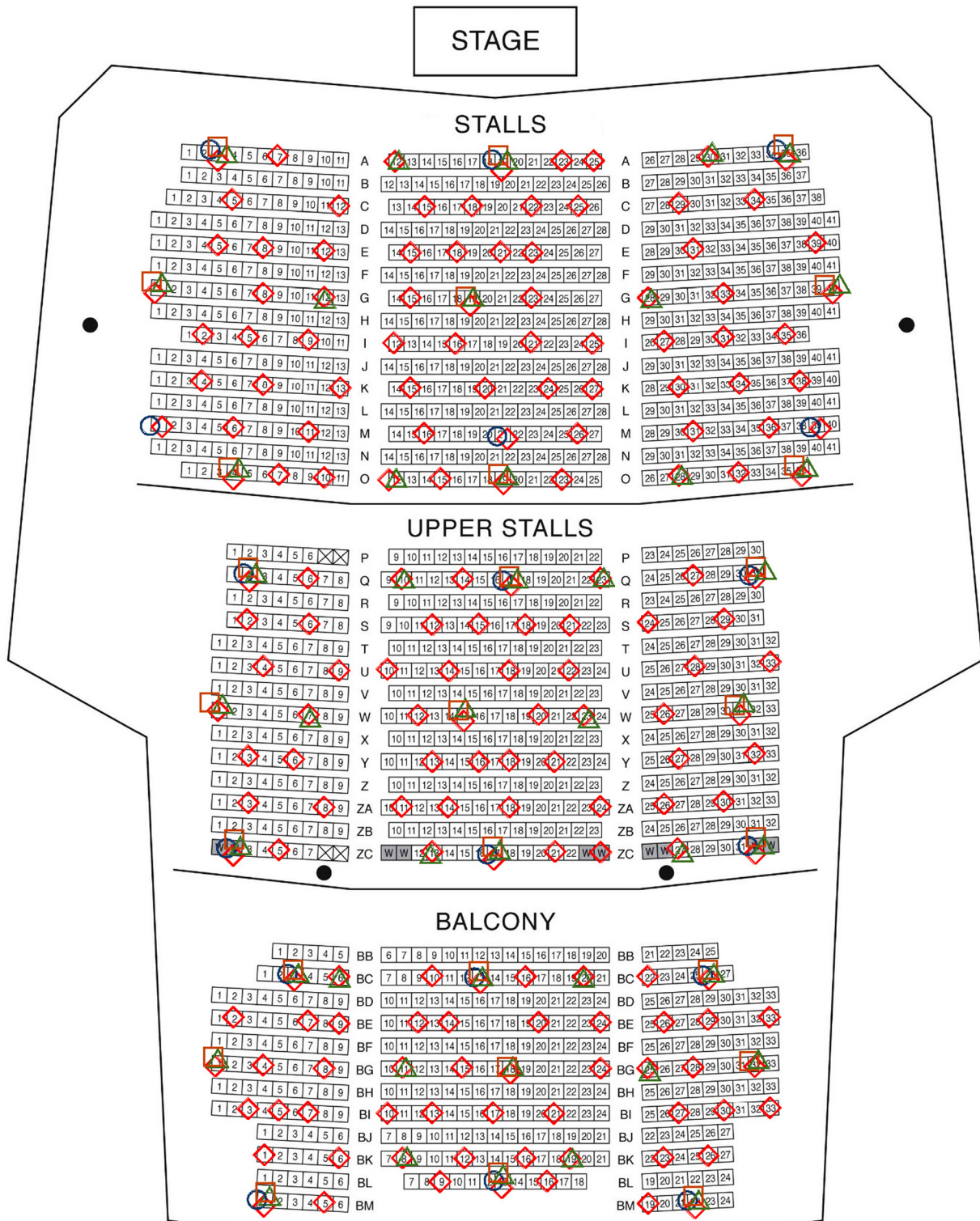


FIG. 5. (Color online) Measurement schemes adopted. \diamond , scheme A; \circ , scheme B; \square , scheme C; \triangle , scheme D.

The inclusion of more data sets under scheme D makes δ a reasonable parameter to be included in the regression modeling as indicated in Table IX. However, it is still the least important one compared to the two angles. The best performing model CD20 consists of a polynomial in ϕ of order higher than that of CA22, probably due to the data sets available for analysis. Model CD22 is the counterpart of

models CA11, CB11, and CC11. It is presented in Table IX for reference only. In fact, regression models with $P(\phi, 5)$ cannot give a standard error lower than that of CD20 (not shown here). Comparing the present results with those of Cheung and Tang,²⁰ it is found that regression models that contain ϕ^2 can perform better than the neural network prediction.

TABLE II. Regression analysis at 95% confidence level for the proscenium stage case of hall A under scheme B.

Model	Regression inputs ^a	Correlation coefficient, R^2	Adjusted R^2	Standard error, ε	F	F_{critical}	Significance
PB01	D, D^2	0.1182	0.0006	0.1966	1.01	3.68	0.389
PB02	D, D^2, ϕ	0.1251	-0.0624	0.2027	0.67	3.34	0.586
PB03	D, D^2, θ	0.1408	-0.0432	0.2009	0.76	3.34	0.533
PB04	D, D^2, δ	0.5016	0.3948	0.1531	4.70	3.34	0.018
PB05	$D, D^2, \phi $	0.7090	0.6466	0.1169	11.37	3.34	0.000
PB06	$D, D^2, \phi , \phi^2 $	0.7177	0.6308	0.1195	8.26	3.18	0.002
PB07	D, D^2, ϕ , θ	0.8043	0.7441	0.0995	13.36	3.18	0.000
PB08	D, D^2, ϕ , δ	0.7134	0.6253	0.1204	8.09	3.18	0.002
PB09	$D, D^2, \phi , P(\theta, 2)$	0.8213	0.7468	0.0990	11.03	3.11	0.000
PB10	$D, D^2, \phi , P(\theta, 3)$	0.8270	0.7327	0.1017	8.77	3.09	0.001
PB11	$D, D^2, \phi , P(\theta, 2), \delta$	0.8285	0.7349	0.1013	8.86	3.09	0.001
PB12	$D, D^2, \phi , P(\theta, 2), P(\delta, 2)$	0.8332	0.7164	0.1047	7.13	3.14	0.003
PB13	$D, D^2, \phi , P(\theta, 2), P(\delta, 3)$	0.8333	0.6852	0.1104	5.63	3.23	0.009

^a $P(x, n)$, polynomial in x of order n .

Figure 7 shows the distributions of Δ and $|\Delta|$ under the concert setting. The results of models CA11 and CD22 are included as they are the counterparts of models CB11 and CC11, which are the best performers under schemes B and C. Comparing the results of models CA11 with those of the best performer under scheme A, model CA22, the former model results in a wider band between the 10th and the 90th percentiles of the residues [Fig. 7(a)]. This gives rise to the higher root-mean-square residue of model CA11 than model CA22 presented in Fig. 7(b). For the pair of models CD20 and CD22, the width between the 25th and 75th residue percentiles of the former is shorter and the corresponding median of residue is also lower [Fig. 7(a)]. The slightly larger root-mean-square residue of CD20 than CD22, presented in Fig. 7(b), implies that there is a small proportion of model CD20 predictions that deviates relatively largely from the measurements. The shorter width between the $|\Delta|$ error bars of model CD22 in Fig. 7(b) indicates that this is the case. However, the difference between models CD20 and CD22 predictions is not significant, suggesting that the latter is an acceptable choice of prediction model although its standard error is not as low as the former. It should also be noted that all the models presented in Fig. 7 outperform, significantly,

the neural network model of Cheung and Tang²⁰ in terms of deviations between predictions and measurements when all the 182 data sets are considered together.

The regression models CA11, CB11, CC11, and CD22 are presented in Table V. Again, they are similar, but the coefficients are quite different although the signs of the coefficients, except that of D^2 of model CD22, are the same. However, the sign of D^2 coefficient of model CD22 suggests that the IACC_{E3} decreases monotonically with D , which is in no conflict with those suggested by the other regression models in the present range of D , except at values near to its upper boundary where the negative coefficient of θ helps reduce the IACC_{E3} . It can be concluded that scheme C appears very satisfactory for IACC_{E3} distribution prediction for a balance between manpower and prediction accuracy.

C. Model validation

The results of hall B of Cheung and Tang²⁰ are used here for model validation. Hall B is a fan-shaped performance hall with a smaller seating capacity. There are 84 measurement data sets. The layout and dimensions of hall B can be found in Cheung and Tang²⁰ and, thus, are not presented

TABLE III. Regression analysis at 95% confidence level for the proscenium stage case of hall A under scheme C.

Model	Regression inputs ^a	Correlation coefficient, R^2	Adjusted R^2	Standard error, ε	F	F_{critical}	Significance
PC01	D, D^2	0.1818	0.1136	0.1605	2.67	3.40	0.090
PC02	D, D^2, ϕ	0.1908	0.0853	0.1631	1.81	3.03	0.174
PC03	D, D^2, θ	0.1990	0.0945	0.1622	1.90	3.03	0.157
PC04	D, D^2, δ	0.3049	0.2143	0.1511	3.36	3.03	0.036
PC05	$D, D^2, \phi $	0.6922	0.6521	0.1006	17.24	3.03	0.000
PC06	$D, D^2, \phi , \phi^2 $	0.6922	0.6363	0.1028	12.37	2.82	0.000
PC07	D, D^2, ϕ , θ	0.7574	0.7133	0.0913	17.17	2.82	0.000
PC08	D, D^2, ϕ , δ	0.6928	0.6369	0.1027	12.04	2.82	0.000
PC09	$D, D^2, \phi , P(\theta, 2)$	0.7760	0.7226	0.0899	14.55	2.68	0.000
PC10	$D, D^2, \phi , P(\theta, 3)$	0.7764	0.7093	0.0919	11.57	2.60	0.000
PC11	$D, D^2, \phi , P(\theta, 2), \delta$	0.7764	0.7093	0.0919	11.57	2.60	0.000
PC12	$D, D^2, \phi , P(\theta, 2), P(\delta, 2)$	0.7769	0.6947	0.0942	9.45	2.54	0.000
PC13	$D, D^2, \phi , P(\theta, 2), P(\delta, 3)$	0.7813	0.6842	0.0958	8.04	2.51	0.000

^a $P(x, n)$, polynomial in x of order n .

TABLE IV. Regression analysis at 95% confidence level for the proscenium stage case of hall A under scheme D.

Model	Regression inputs ^a	Correlation coefficient, R^2	Adjusted R^2	Standard error, ε	F	F_{critical}	Significance
PD01	D, D^2	0.2873	0.2534	0.1329	8.47	3.21	0.001
PD02	D, D^2, ϕ	0.3030	0.2519	0.1330	5.94	2.83	0.002
PD03	D, D^2, θ	0.3205	0.2708	0.1314	6.45	2.83	0.001
PD04	D, D^2, δ	0.5563	0.5238	0.1061	17.13	2.83	0.000
PD05	$D, D^2, \phi $	0.6825	0.6593	0.0898	29.38	2.83	0.000
PD06	$D, D^2, \phi , \phi^2 $	0.6882	0.6571	0.0908	22.08	2.61	0.000
PD07	D, D^2, ϕ , θ	0.7598	0.7358	0.0791	31.63	2.61	0.000
PD08	D, D^2, ϕ , δ	0.6825	0.6508	0.0909	21.50	2.61	0.000
PD09	$D, D^2, \phi , P(\theta, 2)$	0.7871	0.7598	0.0754	28.84	2.46	0.000
PD10	$D, D^2, \phi , P(\theta, 3)$	0.7883	0.7549	0.0762	23.59	2.35	0.000
PD11	$D, D^2, \phi , P(\theta, 2), \delta$	0.7873	0.7537	0.0763	23.44	2.35	0.000
PD12	$D, D^2, \phi , P(\theta, 2), P(\delta, 2)$	0.7875	0.7472	0.0773	19.58	2.27	0.000
PD13	$D, D^2, \phi , P(\theta, 2), P(\delta, 3)$	0.7935	0.7476	0.0773	17.29	2.21	0.000

^a $P(x, n)$, polynomial in x of order n .

here. Unlike hall A, hall B is basically acoustically symmetrical under both the proscenium stage and concert hall settings. The results obtained using scheme C are adopted here as it is shown in Secs. III A and III B that it is a better measurement approach in terms of measurement manpower and prediction accuracy. In fact, the results obtained using scheme D are largely in line with the scheme C results (not presented here). One should note that only the forms of the models are the targets in this validation. As mentioned before, the various coefficients in the models are not of concern, as they are expected to be functions of hall details, absorption, and many other design parameters, which can vary substantially from hall to hall.

Table X illustrates the performances of the regression models for predicting $IACC_{E3}$ in hall B using the same model generation approach adopted in the hall A analysis. Only the results of more important models are presented. In this acoustically symmetrical hall B, $|\phi|$ is better than just ϕ regardless of the hall setting. Together with the results of the hall A under the proscenium stage setting, it appears that the magnitude of the azimuthal angle is more important than its actual values and any polynomials in ϕ for acoustically symmetrical halls (which should be the usual design).

For hall B under the proscenium stage setting, the best performing model is BC09P in term of standard error obtained using the 27 measurement points of scheme C. The models BC11P and BC12P give very similar performance. Model BC11P is the counterpart of PC09 (for hall A). However, the root-mean-square residue $|\Delta|$ of model BC11P (and also BC12P) is better than that of BC09P when all the measurement data in hall B are included. This will be further discussed later together with Fig. 8. Under the concert hall setting, model BC11C, which is the same as BC11P, performs the best in terms of standard error. In this acoustically symmetrical hall B, models with polynomial in ϕ , such as model BC15C, which is the counterpart of CD22 (for hall A), do not perform so well. Apart from the relatively larger standard error, the significance of the regression is also marginal.

Figure 8 shows the $|\Delta|$ distributions of models BC09P, BC11P, BC12P, BC11C, BC14C, and BC15C, and the corresponding standard deviations of Δ . All 84 data sets in hall B are included. Again, all these models, even those involving polynomials in ϕ , outperform the neural network approach of Cheung and Tang²⁰ in the prediction of $IACC_{E3}$ in terms of the standard deviation of residue.

Although model BC09P results in the lowest standard error for the scheme C data and can predict relatively accurately at many surveyed locations in hall B, it gives rise to large variation of prediction error, resulting in a median of $|\Delta|$ very similar to that of model BC11P and a root-mean-square residue Δ even lower than that of model BC11P. Therefore, models BC11P and BC12P are good alternatives. For hall B under concert hall setting, model BC11C performs the best in terms of both the standard error and $|\Delta|$.

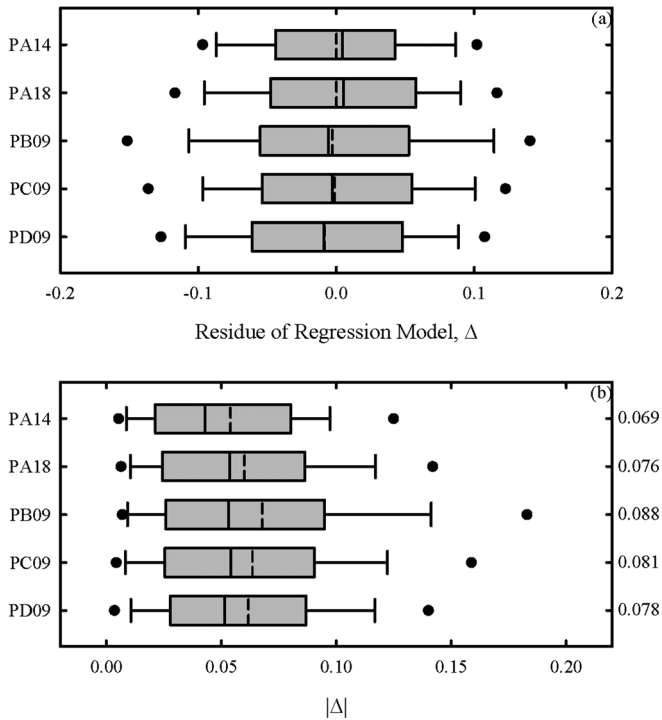


FIG. 6. Regression model residue distributions of hall A under the proscenium stage setting. (a) Δ ; (b) $|\Delta|$. ●, 5th and 95th percentiles; error bars, 10th and 90th percentiles; box edges, 25th and 75th percentiles; vertical lines within boxes, median; vertical dashed lines, mean values.

TABLE V. Coefficients of the regression models under concert hall setting of hall A.

Model	Regression formula
PA18	$IACC_{E3} = 3.0932 - 6.4414D + 4.0528D^2 - 0.7924 \phi + 0.7952\theta - 2.0660\theta^2$
PB09	$IACC_{E3} = 2.6506 - 5.1556D + 3.2831D^2 - 1.1264 \phi + 0.5021\theta - 1.8102\theta^2$
PC09	$IACC_{E3} = 2.5608 - 5.0434D + 3.2274D^2 - 0.9094 \phi + 0.5076\theta - 1.6331\theta^2$
PD09	$IACC_{E3} = 2.7028 - 5.4238D + 3.4401D^2 - 0.8701 \phi + 0.5743\theta - 1.7504\theta^2$
CA11	$IACC_{E3} = 0.9611 - 0.3347D + 0.1290D^2 + 0.7475\phi - 3.9590\phi^2 - 6.9810\phi^3 + 11.1280\phi^4 + 26.5727\phi^5 - 0.1203\theta$
CB11	$IACC_{E3} = 0.9976 - 0.4602D + 0.2829D^2 + 0.9617\phi - 4.3798\phi^2 - 15.2082\phi^3 + 13.1168\phi^4 + 57.5141\phi^5 - 0.2351\theta$
CC11	$IACC_{E3} = 1.1097 - 0.7803D + 0.4697D^2 + 0.7019\phi - 3.8395\phi^2 - 8.3954\phi^3 + 9.9697\phi^4 + 31.6655\phi^5 - 0.1586\theta$
CD22	$IACC_{E3} = 0.8544 - 0.0520D - 0.0317D^2 + 0.6513\phi - 4.3352\phi^2 - 6.2659\phi^3 + 12.9996\phi^4 + 23.3590\phi^5 - 0.1725\theta$

TABLE VI. Regression analysis at 95% confidence level for the concert setting under scheme A.

Model	Regression inputs ^a	Correlation coefficient, R^2	Adjusted R^2	Standard error, ε	F	$F_{critical}$	Significance
CA01	D, D^2	0.0168	0.0058	0.1342	1.53	19.49	0.220
CA02	D, D^2, ϕ	0.3466	0.3356	0.1098	31.47	8.54	0.000
CA03	D, D^2, θ	0.0222	0.0057	0.1343	1.35	8.54	0.261
CA04	D, D^2, δ	0.2086	0.1953	0.1209	15.64	8.54	0.000
CA05	$D, D^2, P(\phi, 2)$	0.7410	0.7351	0.0693	126.57	5.65	0.000
CA06	$D, D^2, P(\delta, 2)$	0.2143	0.1965	0.1207	12.07	5.65	0.000
CA07	$D, D^2, P(\phi, 3)$	0.7578	0.7509	0.0672	110.12	4.39	0.000
CA08	$D, D^2, P(\phi, 4)$	0.7912	0.7841	0.0626	110.54	3.69	0.000
CA09	$D, D^2, P(\phi, 5)$	0.8060	0.7982	0.0605	103.24	3.26	0.000
CA10	$D, D^2, P(\phi, 6)$	0.8065	0.7976	0.0606	90.15	2.96	0.000
CA11	$D, D^2, P(\phi, 5), \theta$	0.8255	0.8174	0.0575	102.30	2.96	0.000
CA12	$D, D^2, P(\phi, 5), \delta$	0.8060	0.7970	0.0607	89.83	2.96	0.000
CA13	$D, D^2, P(\phi, 5), \theta, \delta$	0.8255	0.8164	0.0577	90.44	2.74	0.000
CA14	$D, D^2, P(\phi, 5), P(\theta, 2)$	0.8331	0.8244	0.0564	95.38	2.74	0.000
CA15	$D, D^2, P(\phi, 5), P(\theta, 3)$	0.8340	0.8243	0.0565	85.90	2.57	0.000
CA16	$D, D^2, P(\phi, 5), P(\theta, 2), \delta$	0.8337	0.8239	0.0565	85.70	2.57	0.000
CA17	$D, D^2, P(\phi, 5), P(\theta, 2), P(\delta, 2)$	0.8337	0.8229	0.0567	77.48	2.44	0.000
CA18	$D, D^2, P(\phi, 5), P(\theta, 2), P(\delta, 3)$	0.8349	0.8232	0.0566	71.23	2.33	0.000
CA19	$D, D^2, P(\phi, 5), P(\theta, 2), P(\delta, 4)$	0.8416	0.8293	0.0556	68.64	2.24	0.000
CA20	$D, D^2, P(\phi, 5), P(\theta, 2), P(\delta, 5)$	0.8478	0.8350	0.0547	66.44	2.16	0.000
CA21	$D, D^2, P(\phi, 5), P(\theta, 2), P(\delta, 6)$	0.8489	0.8352	0.0547	62.17	2.10	0.000
CA22	$D, D^2, P(\phi, 5), P(\theta, 2), P(\delta, 7)$	0.8515	0.8371	0.0544	59.14	2.05	0.000
CA23	$D, D^2, P(\phi, 5), P(\theta, 2), P(\delta, 8)$	0.8520	0.8367	0.0544	55.34	1.69	0.000

^a $P(x, n)$, polynomial in x of order n .

TABLE VII. Regression analysis at 95% confidence level for the concert setting under scheme B.

Model	Regression inputs ^a	Correlation coefficient, R^2	Adjusted R^2	Standard error, ε	F	$F_{critical}$	Significance
CB01	D, D^2	0.0581	-0.0675	0.1547	0.46	3.68	0.639
CB02	D, D^2, ϕ	0.2710	0.1148	0.1409	1.74	3.34	0.206
CB03	D, D^2, θ	0.0627	-0.1382	0.1597	0.31	3.34	0.816
CB04	D, D^2, δ	0.2874	0.1347	0.1393	1.88	3.34	0.179
CB05	$D, D^2, P(\phi, 2)$	0.7399	0.6599	0.0873	9.25	3.18	0.001
CB06	$D, D^2, P(\delta, 2)$	0.3136	0.1024	0.1418	1.48	3.18	0.263
CB07	$D, D^2, P(\phi, 3)$	0.7492	0.6447	0.0892	7.17	3.11	0.003
CB08	$D, D^2, P(\phi, 4)$	0.7836	0.6655	0.0866	6.64	3.09	0.004
CB09	$D, D^2, P(\phi, 5)$	0.8612	0.7640	0.0727	8.86	3.14	0.001
CB10	$D, D^2, P(\phi, 6)$	0.8622	0.7396	0.0764	7.04	3.23	0.004
CB11	$D, D^2, P(\phi, 5), \theta$	0.9309	0.8694	0.0541	15.15	3.23	0.000
CB12	$D, D^2, P(\phi, 5), \delta$	0.8612	0.7379	0.0766	6.98	3.23	0.004
CB13	$D, D^2, P(\phi, 5), \theta, \delta$	0.9314	0.8542	0.0572	12.06	3.39	0.001
CB14	$D, D^2, P(\phi, 5), P(\theta, 2)$	0.9376	0.8674	0.0545	13.35	3.39	0.000
CB15	$D, D^2, P(\phi, 5), P(\theta, 3)$	0.9376	0.8486	0.0583	10.53	3.64	0.002
CB16	$D, D^2, P(\phi, 5), P(\theta, 2), \delta$	0.9377	0.8486	0.0583	10.53	3.64	0.002
CB17	$D, D^2, P(\phi, 5), P(\theta, 2), P(\delta, 2)$	0.9377	0.8235	0.0629	8.21	4.03	0.009

^a $P(x, n)$, polynomial in x of order n .

TABLE VIII. Regression analysis at 95% confidence level for the concert setting under scheme C.

Model	Regression inputs ^a	Correlation coefficient, R^2	Adjusted R^2	Standard error, ε	F	F_{critical}	Significance
CC01	D, D^2	0.0431	-0.0366	0.1508	0.54	3.40	0.589
CC02	D, D^2, ϕ	0.3033	0.2124	0.1314	3.34	3.03	0.037
CC03	D, D^2, θ	0.0451	-0.0795	0.1539	0.36	3.03	0.781
CC04	D, D^2, δ	0.3019	0.2108	0.1316	3.12	3.03	0.038
CC05	$D, D^2, P(\phi, 2)$	0.7972	0.7604	0.0725	21.63	2.82	0.000
CC06	$D, D^2, P(\delta, 2)$	0.3028	0.1974	0.1327	2.60	2.82	0.064
CC07	$D, D^2, P(\phi, 3)$	0.8075	0.7616	0.0723	17.61	2.68	0.000
CC08	$D, D^2, P(\phi, 4)$	0.8237	0.7709	0.0709	15.58	2.60	0.000
CC09	$D, D^2, P(\phi, 5)$	0.8453	0.7883	0.0681	14.83	2.54	0.000
CC10	$D, D^2, P(\phi, 6)$	0.8489	0.7818	0.0692	12.64	2.51	0.000
CC11	$D, D^2, P(\phi, 5), \theta$	0.8779	0.8234	0.0622	16.18	2.51	0.000
CC12	$D, D^2, P(\phi, 5), \delta$	0.8481	0.7806	0.0694	12.56	2.51	0.000
CC13	$D, D^2, P(\phi, 5), \theta, \delta$	0.8813	0.8185	0.0631	14.03	2.49	0.000
CC14	$D, D^2, P(\phi, 5), P(\theta, 2)$	0.8807	0.8175	0.0633	13.94	2.49	0.000
CC15	$D, D^2, P(\phi, 5), P(\theta, 2), \delta$	0.8871	0.8044	0.0655	10.72	2.49	0.000

^a $P(x, n)$, polynomial in x of order n .

distribution. Together with the results of hall A, it can be concluded that models of the form similar to that of model PC09 (thus, also BC11P and BC11C) are suitable for predicting $IACC_{E3}$ in an acoustically symmetrical hall. The forms of model PC10 (same as BC12P and BC12C) also fit for the purpose. The difference between PC09 and PC10 is insignificant.

One can observe from the performances of models BC11C and BC15C and the results of hall A that polynomials in ϕ may be more useful when the hall is acoustically asymmetrical. However, this is not a common hall design. It is conjectured that the order of the polynomial would depend

on the degree of acoustical asymmetry. For hall B, the best regression model that involves polynomial of ϕ appears to be model BC14C. It consists of a fourth-order polynomial in ϕ . Those cases with the second- and sixth-order ϕ polynomials are not as good (not shown here). The results of this validation seem to suggest that the order of such a polynomial may vary from hall to hall. However, the present results indicate that such change may not be substantial as there is only a one-order difference between an asymmetrical concert setting hall A and a symmetrical hall B. This is left to further investigation. It is also expected that the degree of asymmetry should be low in real halls.

TABLE IX. Regression analysis at 95% confidence level for the concert setting under Scheme D.

Model	Regression inputs ^a	Correlation coefficient, R^2	Adjusted R^2	Standard error, ε	F	F_{critical}	Significance
CD01	D, D^2	0.0012	-0.0463	0.1418	0.03	3.22	0.975
CD02	D, D^2, ϕ	0.3571	0.3100	0.1151	7.59	2.83	0.000
CD03	D, D^2, θ	0.0084	-0.0644	0.1430	0.12	2.83	0.950
CD04	D, D^2, δ	0.2369	0.1811	0.1254	4.24	2.83	0.011
CD05	$D, D^2, P(\phi, 2)$	0.7257	0.6982	0.0761	24.45	2.61	0.000
CD06	$D, D^2, P(\delta, 2)$	0.2888	0.2177	0.1226	4.06	2.61	0.007
CD07	$D, D^2, P(\phi, 3)$	0.7352	0.7013	0.0758	21.66	2.46	0.000
CD08	$D, D^2, P(\phi, 4)$	0.7857	0.7518	0.0691	23.22	2.35	0.000
CD09	$D, D^2, P(\phi, 5)$	0.7964	0.7579	0.0682	20.68	2.27	0.000
CD10	$D, D^2, P(\phi, 6)$	0.8105	0.7684	0.0667	19.25	2.21	0.000
CD11	$D, D^2, P(\phi, 7)$	0.8329	0.7899	0.0635	19.38	2.16	0.000
CD12	$D, D^2, P(\phi, 8)$	0.8329	0.7919	0.0632	17.75	2.12	0.000
CD13	$D, D^2, P(\phi, 9)$	0.8409	0.7879	0.0638	15.86	2.09	0.000
CD14	$D, D^2, P(\phi, 8), \theta$	0.8802	0.8402	0.0554	21.72	2.09	0.000
CD15	$D, D^2, P(\phi, 8), \delta$	0.8393	0.7857	0.0641	15.66	2.09	0.000
CD16	$D, D^2, P(\phi, 8), \theta, \delta$	0.8802	0.8353	0.0562	19.60	2.07	0.000
CD17	$D, D^2, P(\phi, 8), P(\theta, 2)$	0.8831	0.8392	0.0556	20.14	2.07	0.000
CD18	$D, D^2, P(\phi, 8), P(\theta, 3)$	0.8831	0.8341	0.0565	18.02	2.05	0.000
CD19	$D, D^2, P(\phi, 8), P(\theta, 2), \delta$	0.8838	0.8350	0.0563	18.13	2.05	0.000
CD20	$D, D^2, P(\phi, 8), P(\theta, 2), P(\delta, 2)$	0.9010	0.8547	0.0528	19.49	2.04	0.000
CD21	$D, D^2, P(\phi, 8), P(\theta, 2), P(\delta, 3)$	0.9010	0.8498	0.0537	17.59	2.03	0.000
CD22	$D, D^2, P(\phi, 5), \theta$	0.8410	0.8056	0.0611	23.79	2.21	0.000

^a $P(x, n)$, polynomial in x of order n .

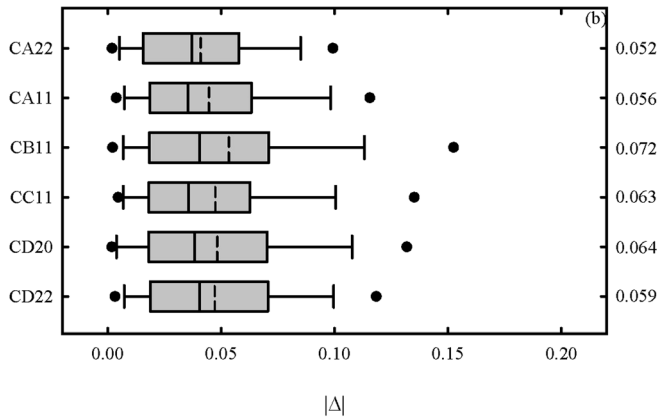
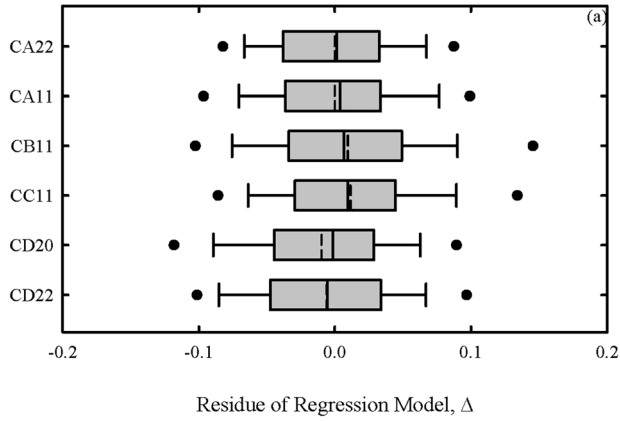


FIG. 7. Regression model residue distributions of hall A under concert hall setting. (a) Δ ; (b) $|\Delta|$. Legends are the same as those for Fig. 6.

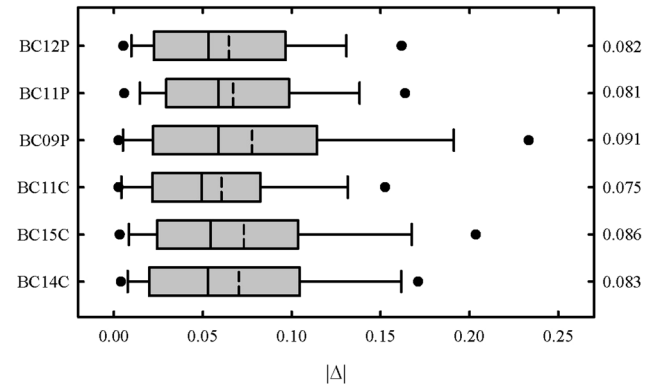


FIG. 8. $|\Delta|$ distributions of hall B. Legends are the same as those for Fig. 6.

D. Application remarks

The regression models in this study start with a quadratic formula in D . This is done because of the availability of data obtained from an earlier intensive measurement inside the hall. However, it is certainly not the case in practice. In fact, the results obtained with a linear D are quite close to those presented (not shown here). There is evidence also in existing literature that the early IACCs decrease with increasing distance from the sound source except at locations relatively close to solid boundaries inside halls with aspect ratios similar to the present one (for instance, Hotehama *et al.*²⁷ and Sakurai *et al.*²⁸). Therefore, any simple function that decreases monotonically with increasing D should be useful in the formation of the regression model. The very simple quadratic formula in D , therefore, is a logical choice. An example is illustrated using hall B during the validation where no prior correlation

TABLE X. Regression analysis at 95% confidence level for hall B under scheme C.

Hall setting	Model	Regression inputs ^a	Correlation coefficient, R^2	Adjusted R^2	Standard error, ε	F	F_{critical}	Significance
Proscenium	BC01P	D, D^2, ϕ	0.1319	0.0187	0.0978	1.17	2.83	0.345
	BC02P	$D, D^2, \phi $	0.5890	0.5354	0.0673	10.99	2.83	0.000
	BC03P	$D, D^2, P(\phi , 2)$	0.6640	0.6029	0.0622	10.87	2.61	0.000
	BC04P	D, D^2, ϕ , θ	0.6138	0.5436	0.0667	8.74	2.61	0.000
	BC05P	$D, D^2, P(\phi , 3)$	0.6641	0.5842	0.0637	8.31	2.46	0.000
	BC06P	$D, D^2, P(\phi , 2), \theta$	0.6800	0.6038	0.0622	8.92	2.46	0.000
	BC07P	$D, D^2, P(\phi , 2), P(\theta, 2)$	0.7408	0.6631	0.0573	9.53	2.35	0.000
	BC08P	$D, D^2, P(\phi , 2), P(\theta, 3)$	0.7615	0.6734	0.0564	8.67	2.27	0.000
	BC09P	$D, D^2, P(\phi , 2), P(\theta, 4)$	0.8520	0.7862	0.0457	12.95	2.21	0.000
	BC10P	$D, D^2, P(\phi , 2), P(\theta, 5)$	0.8521	0.7738	0.0470	10.88	2.15	0.000
	BC11P	$D, D^2, \phi , P(\theta, 2)$	0.6531	0.5706	0.0647	7.91	2.46	0.000
	BC12P	$D, D^2, \phi , P(\theta, 3)$	0.6839	0.5890	0.0633	7.21	2.35	0.000
	BC13P	$D, D^2, \phi , P(\theta, 4)$	0.6986	0.5876	0.0634	6.29	2.27	0.001
Concert	BC01C	D, D^2, ϕ	0.0218	-0.1058	0.1149	0.17	2.83	0.915
	BC02C	$D, D^2, \phi $	0.6517	0.6063	0.0685	14.35	2.83	0.000
	BC03C	$D, D^2, P(\phi , 2)$	0.6586	0.5965	0.0694	10.61	2.61	0.000
	BC04C	D, D^2, ϕ , θ	0.6628	0.6015	0.0690	10.81	2.61	0.000
	BC11C	$D, D^2, \phi , P(\theta, 2)$	0.7145	0.6466	0.0649	10.51	2.46	0.000
	BC12C	$D, D^2, \phi , P(\theta, 3)$	0.7275	0.6458	0.0650	8.90	2.35	0.000
	BC14C	$D, D^2, P(\phi, 3), \theta$	0.5647	0.4341	0.0822	4.32	2.35	0.006
	BC15C	$D, D^2, P(\phi, 4), \theta$	0.6103	0.4667	0.0798	4.25	2.27	0.006
	BC16C	$D, D^2, P(\phi, 5), \theta$	0.6147	0.4435	0.0815	3.59	2.21	0.012

^a $P(x, n)$, polynomial in x of order n .

between D and $IACC_{E3}$ has to be done. One should also note that though the symmetry of the sound field inside the surveyed hall is known beforehand, it is never a parameter to consider in the formation of the regression models. One can test the performance of ϕ and $|\phi|$ in the first place.

It is observed that the path difference δ is only useful when ϕ is not included in the modeling and is basically of no use when both ϕ and θ are taken into account. This may be due to the fact that only one hall is investigated in this study. As δ contains information of the physical nearfield hall layout which can affect the acoustics of a hall,^{19,29} it may be useful when data of many halls are analyzed together. It is left to further investigation.

IV. CONCLUSIONS

In this study, the previous binaural measurement results of the authors obtained in two multi-purpose performance halls are re-analyzed in an attempt to establish a systematic framework for predicting the early IACCs through simple regression models with as little geometrical hall parameters and measurements as possible. The geometrical parameters investigated are the source-to-receiver distance, the azimuthal and elevation angles of the receiver relative to the source, and the path difference between the direct sound and the first reflection. For simplicity, the regression models so generated are formed by linear combinations of polynomials of these parameters and no cross products of different parameters are considered. A procedure is also proposed for the generation of regression models.

Both proscenium stage and concert hall settings are included in the present study. For both settings, a scheme where the measurement points are roughly arranged in three 3-by-3 matrices each spans over one sub-area of the hall appears to be effective in terms of measurement workload and accuracy of regression prediction. The regression models generated give much better predictions than the neural network approach of the authors once the source-to-receiver distance, azimuthal, and elevation angles are included. However, the best performing regression models for symmetrical and asymmetrical halls under this measurement scheme are different. For the symmetrical cases, no matter if it is the proscenium stage case or the concert hall case, a model that consists of quadratic polynomials in source-to-receiver distance and elevation angle and a linear function of the azimuthal angle magnitude appears to be a very good choice. The best regression model for the asymmetrical concert setting is made up of a linear function of elevation angle, a polynomial in azimuthal angle, and a quadratic function of source-to-receiver distance. However, such a model is still able to give acceptable performance when the concert hall is acoustically symmetrical. Since asymmetrical hall design is uncommon, further validation is required.

There is evidence that the stronger and probably more organized sound radiation in the presence of the acoustic shells in an acoustically asymmetrical concert hall has largely increased the influence of azimuthal angle on the early sound and its binaural correlation. The path difference is not included in all the best performing models, and is also

not important once both the azimuthal and elevation angles are included in the regression model.

It should be noted that the development of a universal regression formula with fixed coefficients for general application is never an objective of this study. It is believed that the abovementioned measurement scheme, which is suitable for studies in both rectangular and fan-shaped halls, together with the present proposed regression model generation procedures and the geometrical parameters, should work for halls with simple layouts. The present results show that a simple model for predicting $IACC_{E3}$ to within engineering tolerance in acoustically symmetrical halls is possible.

ACKNOWLEDGMENTS

L.Y.C. is supported by a studentship provided by the Research Committee, The Hong Kong Polytechnic University. The supports from the colleagues of Leisure and Cultural Services Department, the HKSAR (Hong Kong Special Administrative Region) Government are gratefully acknowledged.

- ¹L. L. Beranek, *Concert Halls and Opera Houses*, 2nd ed. (Springer, New York, 2004), pp. 1–640.
- ²M. Barron, *Auditorium Acoustics and Architectural Design*, 2nd ed. (Spon, Oxon, 2010), pp. 1–489.
- ³A. Farina, “Acoustic quality of theatres: Correlations between experimental measures and subjective evaluations,” *Appl. Acoust.* **62**, 889–916 (2001).
- ⁴T. Lokki, J. Pätynen, A. Kuusinen, H. Vertanen, and S. Tervo, “Concert hall assessment with individually elicited attributes,” *J. Acoust. Soc. Am.* **130**, 835–849 (2011).
- ⁵A. Giménez, R. M. Cibrián, S. Girón, T. Zamarreño, J. J. Sendra, A. Vela, and F. Daumal, “Questionnaire survey to quality the acoustics of Spanish concert halls,” *Acta Acust. Acust.* **97**, 949–965 (2011).
- ⁶M. Barron, “Balcony overhangs in concert auditorium,” *J. Acoust. Soc. Am.* **98**, 2580–2589 (1995).
- ⁷L. L. Beranek and T. Hidaka, “Sound absorption in concert halls by seats, occupied and unoccupied, and by the hall’s interior surfaces,” *J. Acoust. Soc. Am.* **104**, 3169–3177 (1998).
- ⁸R. Thiele, “Directional and chronological distribution of sound pressure in confined spaces,” *Acustica* **3**, 291–302 (1953) (in German).
- ⁹W. Reichardt, O. Abdel Alim, and W. Schmidt, “Dependence of the boundary between useful and useless clarity of musicals on reverberation and the use of reverberation time,” *Appl. Acoust.* **7**, 243–264 (1974) (in German).
- ¹⁰Y. Ando and M. Imamura, “Subjective preference tests for sound fields in concert halls simulated by the aid of a computer,” *J. Sound Vib.* **65**, 229–239 (1979).
- ¹¹M. Barron and A. H. Marshall, “Spatial impression due to early lateral reflections in concert halls,” *J. Sound Vib.* **77**, 211–232 (1981).
- ¹²T. Hidaka, L. L. Beranek, and T. Okano, “Interaural cross-correlation, lateral fraction, and low- and high-frequency sound levels as measures of acoustical quality in concert halls,” *J. Acoust. Soc. Am.* **98**, 988–1007 (1995).
- ¹³T. Okano, L. L. Beranek, and T. Hidaka, “Relations among interaural cross-correlation coefficient ($IACC_E$), lateral fraction (LF_E), and apparent source width (ASW) in concert halls,” *J. Acoust. Soc. Am.* **104**, 255–265 (1998).
- ¹⁴A. P. O. Carvalho, “Relations between rapid speech transmission index (RASTI) and other acoustical and architectural measures in churches,” *Appl. Acoust.* **58**, 33–49 (1999).
- ¹⁵S. K. Tang, “Speech related acoustical parameters in classrooms and their relationships,” *Appl. Acoust.* **69**, 1318–1331 (2008).
- ¹⁶M. Barron and L. J. Lee, “Energy relations in concert auditoriums. I,” *J. Acoust. Soc. Am.* **84**, 618–628 (1988).
- ¹⁷U. Berardi, E. Cirillo, and F. Martellotta, “A comparative analysis of acoustic energy models for churches,” *J. Acoust. Soc. Am.* **126**, 1838–1849 (2009).

- ¹⁸R. San Martin and M. Arana, "Predicted and experimental results of acoustic parameters in the new Symphony Hall in Pamplona, Spain," *Appl. Acoust.* **67**, 1–14 (2006).
- ¹⁹J. Nannariello and F. R. Frickle, "A neural-computation method of predicting the early interaural cross-correlation coefficient (IACC_{E3}) for auditoria," *Appl. Acoust.* **63**, 627–641 (2002).
- ²⁰L. Y. Cheung and S. K. Tang, "Neural network predictions of acoustical parameters in multi-purpose performance halls," *J. Acoust. Soc. Am.* **134**, 2049–2065 (2013).
- ²¹L. L. Beranek, "Concert hall acoustics—2008," *J. Audio. Eng. Soc.* **56**, 532–544 (2008).
- ²²DIRAC, "Dual input room acoustics calculator" (Acoustics Engineering, Denmark, 2015, information available at <http://www.acoustics-engineering.com/dirac/dirac.htm> (Last viewed 9/29/2015).
- ²³J. K. Ryu and J. Y. Jeon, "Subjective and objective evaluations of a scatter sound field in a scale model opera house," *J. Acoust. Soc. Am.* **124**, 1538–1549 (2008).
- ²⁴T. Hidaka, L. L. Beranek, S., Masuda, N. Nishihara, and T. Okano, "Acoustical design of the Tokyo Opera City (TOC) concert hall, Japan," *J. Acoust. Soc. Am.* **107**, 340–354 (2000).
- ²⁵P. Evjen, J. S. Bradley, and S. G. Norcross, "The effect of late reflections from above and behind on listener envelopment," *Appl. Acoust.* **62**, 137–153 (2001).
- ²⁶A. Kuusinen, J. Pätynen, S. Tervo, and T. Lokki, "Relationships between preference ratings, sensory profiles, and acoustical measurements in concert halls," *J. Acoust. Soc. Am.* **135**, 239–250 (2014).
- ²⁷T. Hotehama, S. Sato, and Y. Ando, "Dissimilarity judgments in relation to temporal and spatial factors for the sound field in an existing hall," *J. Sound Vib.* **258**, 429–441 (2002).
- ²⁸M. Sakurai, S. Aizawa, Y. Suzumura, and Y. Ando, "A diagnostic system measuring orthogonal factors of sound fields in a scale model of auditorium," *J. Sound Vib.* **232**, 231–237 (2000).
- ²⁹Y. Jurkiewicz, T. Wulfrank, and E. Kahle, "Architectural shape and early acoustic efficiency in concert halls," *J. Acoust. Soc. Am.* **132**, 1253–1256 (2012).