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A PRELIMINARY STUDY TOWARD THE AUTOMATION OF THE PLACEMENT OF ABSORBING SURFACES IN DIFFERENT SPACES

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ABSTRACT

Improving room acoustics can greatly enhance our listening experience in venues, but is often expensive, requiring expert knowledge and installation of treatment material. This study explores using generalised optimisation techniques to recommend acoustic treatments. The proposed method uses random configurations of a parametric room model and its simulated acoustic properties as training data for a linear regression model. An optimisation stage then identifies parameters to minimise or maximise an acoustic property. In this study, positions of absorption panels were optimised in two tasks; 1) Minimise the T30, 2) Acoustically isolate two source-receiver pairs, assessed by a Signal to Noise Ratio (SNR) metric calculated from simulated acoustic data. In task 1, the method generated a panel arrangement which closely resembled literature recommendations, demonstrating the method's potential for producing solutions regarded as optimal. In task 2, the generated arrangement yielded an SNR of 8.0 dB, greater than the best random arrangement from the training data (7.6 dB). This highlighted the method's potential to produce novel designs, instead of simply replicating high-performing training data. The effectiveness of the generalised approach suggests a similar method could be used for less trivial cases, such as furniture positioning, non-acoustic material installations, and seating areas.

Keywords: *optimisation, parametric, regression*

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1. INTRODUCTION

Bad acoustics can make a space very unpleasant, with 79% of people having left a restaurant, cafe or pub because of noise levels [1]. Current solutions employ specialist acoustics companies who survey the space and generally calculate a surface area of acoustic absorption material to install, aiming to reduce the reverberation time (RT) to a target level, with standards such as DIN18041 [2] detailing recommended RT values for different environment uses. Optimising for RT is widely practiced as basic calculations such as the Sabine formula [3] can be used to calculate the required surface areas of absorption material. An established literature of recommendations are then used to determine where to place the material. [4] summarises some of these recommendations as well as the findings from other studies ([2], [5], [6], [7], [8]) which include; large areas of absorption on the ceiling, absorption or diffusion on the rear and/or front walls to combat flutter echoes, and applying absorption in the middle areas of walls. While these recommendations are valuable for many rooms, they are generalised, and focused on 'shoe box' shaped classrooms, meeting rooms, and offices, and so may not apply in unusually shaped rooms such as multi-space restaurants.

To create optimal installations, especially for unusual rooms and more specialist applications, multiple configurations of panels may need to be tested to identify the best. Since this is physically impractical, and the Sabine equations do not take position into consideration, simulations can be used to estimate the acoustic performance of each configuration. Geometrical Acoustics (GA) [9] is widely used and studied for approximating the acoustic properties of spaces. GA is based on modelling the propagation of sound waves as rays interacting with geometry. This also allows for other acoustically significant factors to be modelled, such as sound source locations, soft furnishings, and room shapes, which may have an impact on which configuration is preferable. However, the expertise and time required to set up and perform a simulation often limits the configurations it's possible to explore. For example, [4] uses four and five configurations for their two case study rooms, comparing different distributions of ceiling and wall panels based on recommendations. The expertise required also makes GA inaccessible for everyday spaces, which could benefit from being able to test multiple configurations.

To provide recommendations for unusual spaces and where existing literature may be insufficient, it could be beneficial to be able to automate the simulation of many randomised configurations and use a machine learning approach to learn and predict optimal designs. Inspiration for this comes in part from the field of interpretable machine learning [10], where the trained model itself can be used to yield insights, not just the output. For example, by training an acoustic metric predictor, the model could then be used to reveal which attributes of the room contribute most to that metric, positively or negatively. This has advantages over a more 'black-box' approach in which these insights are often more obscured. This preliminary study will explore a simple example of such an approach by using the statistical feature importances of a linear regression model. Such a method may be used for optimising any acoustically significant objects in occupied spaces, provided they could be expressed in a parametric and meaningful way. For example, a restaurant could model the potential positions of dividing walls in a space parametrically, train a regression model to predict RT based on these parameters (using GA and randomised parameters to create a dataset of acoustic performances), then use the model to gain insights on optimal placements.

For this preliminary study, a conventional optimisation case will be explored to assess if the proposed method produces similar configurations to established recommendations. Therefore, the ideal placement of a fixed number of panels to reduce RT in a large reverberant space will be the subject of optimisation. This study will aim to test the effectiveness of a generalised approach such that in later studies more non-trivial optimisations could be tested. There is currently no system which approaches variable optimisation in room acoustics in this way. Such a system could save spaces significant cost in installing acoustic panels, by presenting affordable alternatives which extract as much performance as possible from constrained resources.

To assess the method, two objectives will be tested, the second beginning to investigate how more case-specific objective goals can be explored by the generalised regression approach:

- Reduce the RT of a space using a budget constrained, fixed number of panels.
- Acoustically isolate two parts of the room from each other, using a Signal to Noise Ratio (SNR) metric.

2. METHOD

The case study room is provided by Dream Factory [1], a company who provides creative spaces for start-ups, including vocal recording rooms, filming sets, and more. The main space of a recently acquired venue, Figure 1, is to be fitted as a video recording space. As such, the large, hard, flat walls, floor and ceiling need to be acoustically damped. Also, they would like to be able to have multiple recording sessions simultaneously in the same room, requiring a degree of acoustic separation between parts of the rooms.

Figure 1. Interior photo of the main space in the new Dream Factory venue.

A 3D model of the room is made, Figure 2, with the locations of the virtual sound source and microphone shown as a sphere and cube respectively. These were the locations used in the on-site acoustic measurements so that the simulation model can be matched to the observed results. Note the smaller left hand room is separate from the main room and not part of the study, but included for illustrative reference of the ground floor layout.

CATT Acoustic v9.1 [2] has been used for all GA simulations, which makes use of a cone tracer to estimate energy echograms and pressure impulse responses. Sound sources are modelled as omni-directional with a

[1] https://www.dreamfactory.ventures
[2] https://www.catt.se/

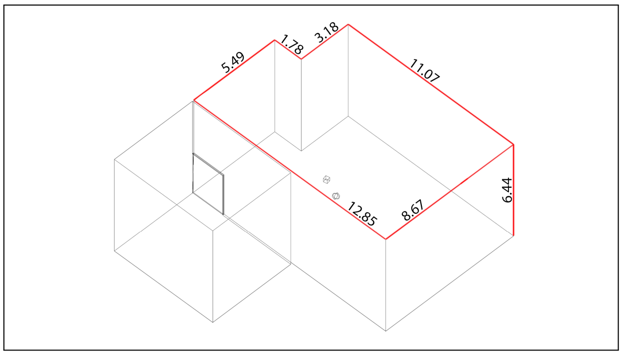

Figure 2. Diagram of sound source and receiver locations, with room dimensions (m)

flat frequency response. First order diffraction is modelled, and a ray count of 10,000 is used which in initial testing showed to be sufficient for stable and converged results. The simulation results, while they are approximations, will be treated as ground truth for the purposes of training and evaluating the optimisation models. There are several metrics for RT; in this study T30 will be used, defined as the time in seconds it takes for the initial dB level of the sound to decay by 60 dB, estimated by measuring the first 30 dB decay. This measure is commonly used in acoustic measurements to extrapolate the RT60 industry standard. The linearly weighted T30 output by CATT Acoustic will be used, which is based on its pressure impulse response estimation.

For all GA simulations, it is necessary to calibrate the material properties so that the simulated T30 value matches a known on-site measurement of T30. Starting with standard material properties found in the CATT library, these were manually refined until the T30 of the simulation closely matched the on-site measurement, 3.39 s and 3.47 s respectively. T30 was also matched for the different frequency bands between the two environments, together with other parameters such as Early Decay Time (EDT). On site acoustic measurements were recorded on a smartphone using a loud clap as an impulse, approximately 0.75 m from the microphone. Audio recordings were processed in the Aurora pluggin for Audacity [3] to calculate T30. This was repeated multiple times to ensure consistent results.

Automation tools for this work have been written in Python and are accessible on GitHub [4]. The modelling of the room was done in the open-source software Blender [5], chosen for its Python API which will be used to control the variable parts of the room (acoustic panels). Python scripts export the necessary data into the appropriate CATT file formats. Data outputted from CATT Acoustic is processed in Python as well.

Acoustic panels come in a range of shapes and sizes. To keep the optimisation task simple for the purposes of this preliminary study, a single panel type will be used. One of the most popular types of panel is the 600 mm x 1200 mm shape, available from multiple manufacturers. To simplify the acoustic panel placement variables in this study, inspiration can be taken from the approach used by [11], where walls were discretised into tiles with absorption coefficients and a least-squares method then found the optimal distribution of absorption coefficients. In this way, all possible acoustic panel locations are preconceived as shown in Figure 3.

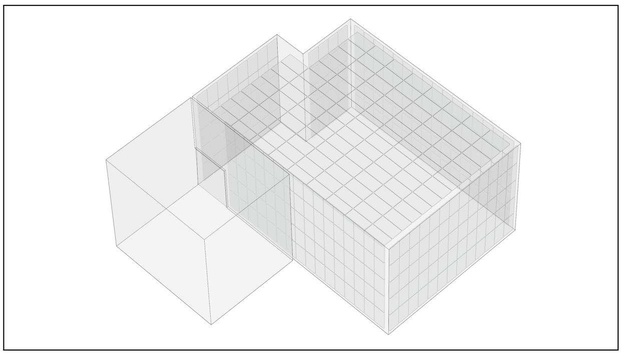

Figure 3. All 397 possible panel positions.

At maximum capacity, the room can hold 397 panels when positioned in this way. The panels are assumed to be suspended from the ceiling, and slightly floating from the walls. The height of the 'false ceiling' of panels is a variable to be optimised, taking values from 4.0 m to 6.0 m in steps of 0.4 m. The floor is modelled as carpeted.

3. INITIAL STUDIES

3.1 Effect of Panel Number and Placement on T30

The first question to address is whether the installation location makes any difference to the performance of acoustic panels. From the possible 397 panels in the room, n panels are chosen at random, for n increasing in steps of

[3] http://www.angelofarina.it/Public/ Aurora-for-Audacity/
[4] https://github.com/otjones/thesis
[5] https://www.blender.org/

25 from 25 to 200. This is repeated 16 times to get multiple different arrangements of the same number of panels. The rooms are then simulated, and the T30 recorded. In this test, the ceiling panel height is fixed at 6.0 m.

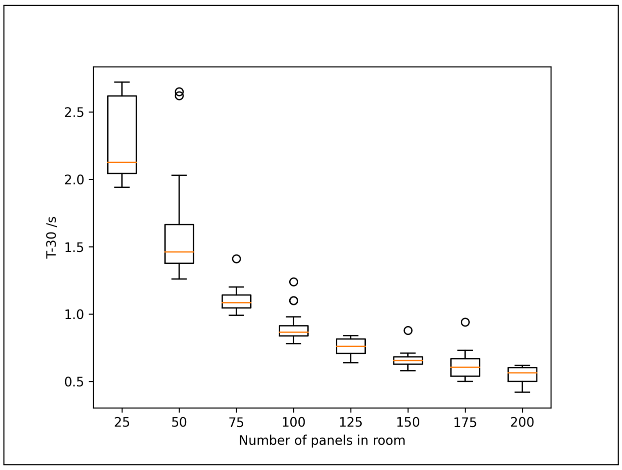

Figure 4. T30 (s) for fixed numbers of acoustic panels, with 16 random configurations for each set quantity.

Figure 4 shows significant variability in the simulated T30 times for each group of n panels, especially for rooms with few panels. In fact, some rooms with 50 panels had a worse T30 than some rooms with only 25 panels, suggesting that some panel installation locations do not help to reduce T30 reverb at all. This suggests that acoustic panel placement can make a significant difference and is something worth optimising, and may also suggest that the locations of other materials are significant too. Based on these data, 75 is chosen as a suitable number of panels for which to find optimal positions.

4. OPTIMISATION

A dataset of randomised panel configurations was generated and simulated as training data for the linear regression model. The objective is then for the model to learn which panels are most effective, and to provide the model with a mechanism for suggesting a new, optimal design. While DIN18041 specifies ideal target T30 times, this optimisation approach is unconstrained in nature, simply suggesting which attributes increase or decrease T30. In this study, should T30 be reduced too much, the number of panels can simply be reduced.

4.1 Data Representation

To efficiently represent the design space, 42 'zones' of panels are designated as shown in Figure 5, where the number of panels present in each zone is recorded as a fraction of the total possible. This approach therefore assumes the slight differences in panel positions within the zone should be small and negligible, and when implementing a generated design, the panels could be put anywhere in their zone. Using this as an input to a linear regression model means the trained coefficients will represent the relative importance of each zone in predicting T30. Coefficients are normalised by the size of the zone, as for example a 0.5 coverage of a zone of 12 is more likely to be effective than a 0.5 coverage of a zone of 8, due to the higher number of panels. This creates 42 variables to describe the state of the room, with an additional 43^{rd} used to describe the false ceiling height.

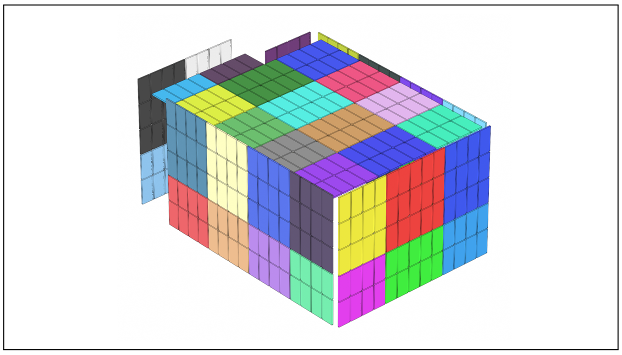

Figure 5. 42 panel zones.

4.2 Linear Regression Model for Reducing T30

The training dataset consists of 1000 random configurations of 75 panels, each recorded as a vector of 43 parameters. For each configuration, the T30 is simulated and recorded. A linear regression model from the SciKit Learn [6] Python library is fitted to this data, using a train-test split of 70:30. The simulated vs predicted T30 times, Figure 6, show a very broad spread and loose correlation, albeit in the correct positive direction with the line of best fit a near 1:1 mapping of simulated to predicted T30 values.

Retraining the model on randomised train-test splits and at different dataset sizes gives an idea of the stability of the model. Dataset sizes from 200 to all 1000 in steps

[6] https://scikit-learn.org/stable

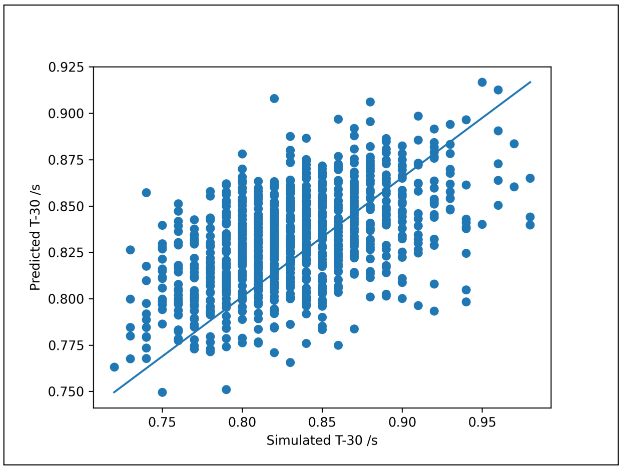

Figure 6. Plot of simulated T30 times vs T30 times predicted by linear regression, all data.

of 100 were each trained 50 times. The R Squared score, Figure 7, shows that at datasets of over 500 configurations the models seem to stabilise, with narrowing spreads and R values just under 0.2, which while low could be sufficient in identifying important zones. A model trained on all 1000 rooms will be used going forward.

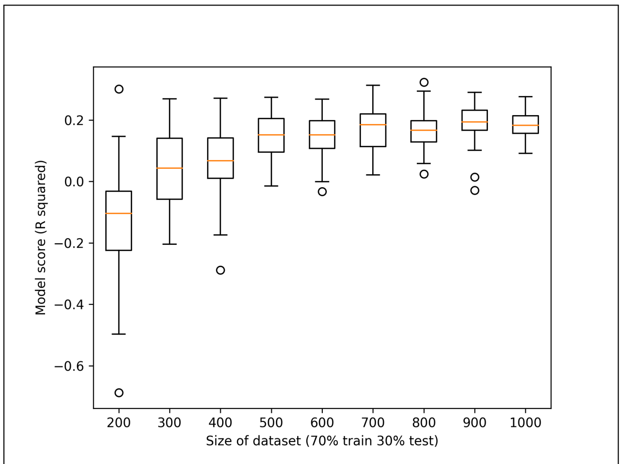

Figure 7. Rate of convergence of linear regression with 50 random samples per dataset size, R squared score from test data shown.

Zones with greater coefficients suggest that adding more panels here increases T30 more so than other zones with smaller coefficients. Therefore, the zones with the smallest coefficients might be the best zones to place panels. Using this concept and applying a 'first past the post' approach, a new room configuration is created by placing panels in these low-coefficient zones until the 75 panel limit is reached. This configuration, Figure 8, gives a simulated T30 of 0.76 s, significantly lower than the best random configuration of 1.0 s, Figure 4. The layout of panels closely matches some of the literature, with large coverage on the two parallel walls perpendicular to the length of the room, and some panels on the other pair of walls. The lack of ceiling panels stands out as going against the recommendations, however, the carpeted floor in the room model may eliminate enough reflections in the vertical direction to lessen the benefit of ceiling panels. It is promising a regression model with only randomised training data could produce a panel layout which makes some intuitive sense, supported by literature recommendations and standards.

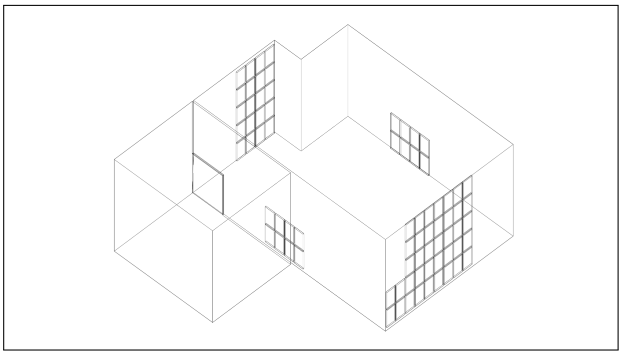

Figure 8. Panel configuration for reducing T30 generated by linear regression based method.

4.3 Considering Each Zone Independently

To inspect the behaviour of the linear regression model, the zones of panels can be simulated one at a time at their full coverage. Figure 9 shows that the reduction in T30 (normalised per panel) varies significantly from zone to zone. If the best zones are taken from this list and populated with 75 panels, the arrangement generated (panels only in the middle of the two walls perpendicular to the length of the room) produces a T30 of 1.08 s, worse than the arrangement produced by the linear regression model. This suggests the linear regression model is not just choosing zones in isolation, but can take all zones into account simultaneously to find optimal balances of zones. The model may therefore have identified a point of diminishing returns of using panels in these zones on the end walls when it starts to suggest panels on the width of the room. It is also worth noting these zones on the width of the room are the closest points on the walls to the virtual sound source and receiver, and so are potentially able to absorb more direct sound than further away panels. This may suggest the linear regression method was able to effectively balance the two concepts of reducing flutter echoes and that panels closest to the source absorb early direct sound before it reflects.

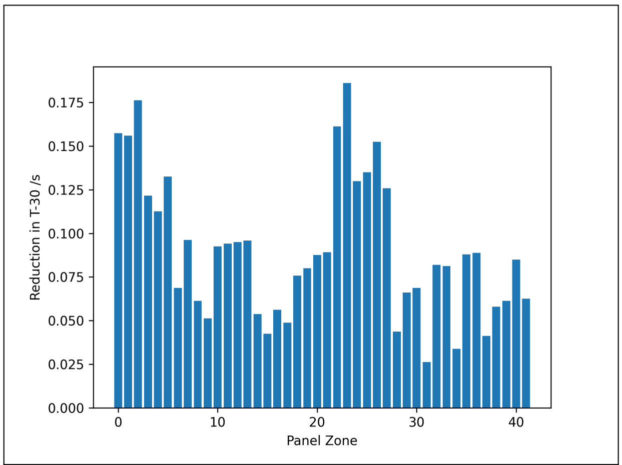

Figure 9. Reduction in T30 (normalised per panel) for each zone in the room.

4.4 Linear Regression Model for Isolating Two Spaces

To test if the proposed method can generalise to different goals, a second optimisation problem is presented. The problem is motivated by the Dream Factory's intention to have two sets of video recordings happening simultaneously in the space at given locations. There are now two sound sources (spheres) and receivers (cubes), a pair on the left and the right, mimicking an actor presenting to a camera a short distance away, Figure 10. The goal is for each of the two receivers to maximise the level of their target source, and minimise the level of the other. In other studies this problem is sometimes referred to as "irrelevant speech" and measured using the Speech Transmission Index (STI) [12]. In this study however, an alternative measure is formed to test optimising for a more use-case specific goal, leveraging the generalised approach. A 'Signal to Noise Ratio', SNR, as calculated in Equation 1 where $R1(S1 - S2)$ denotes the dB SPL level of Source 1 minus Source 2 as heard from Receiver 1.

$$\frac{R1(S1 - S2) + R2(S2 - S1)}{2} \tag{1}$$

For this objective, the highest linear regression coefficients are preferred as the SNR is to be maximised. A new piece of variable geometry is also added to the room setup; two rows of free standing panels (600 mm x 1800 mm) to separate the source-receiver pairs, eliminating direct paths between the two, as shown in Figure 10. These are controlled by parameters for the number of panels in each row, and spacing between each panel. A predefined list of potential combinations is made that fits the space, with the linear regression model aiming to find whether higher or lower values of the four inputs are beneficial, and their importance compared to the wall and ceiling panels. The position of the starting point of the lines of panels is fixed.

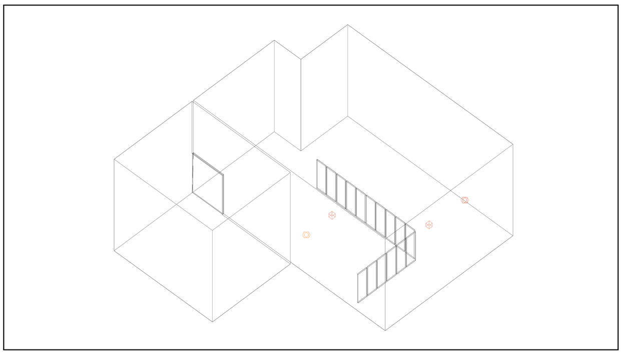

Figure 10. Diagram of source (sphere) - receiver (cube) pairs and example configuration of the floor standing panels added.

A dataset of 392 randomised room configurations is generated, each with a limit of 75 panels. From this dataset, the SNR achieved in the simulations range from 3.1 dB to 7.6 dB. Depending on the random train-test split, the linear regression models achieved R values of 0.3 to 0.5 showing fair correlation, suggesting the model has learnt relatively well which panel configurations improve the SNR. A significantly negative ceiling height coefficient suggests lowering the ceiling increases SNR. In this room configuration therefore, the ceiling is set to its lowest possible height. This also presents one of the key limitations of this approach, where it is only possible to tell whether a parameter should be increased or decreased, with difficulty identifying any ideal intermediary values. Using the coefficients from 16 models fitted to randomised train-test splits, 16 candidate rooms are created to be simulated. One of these configurations had an SNR of 8.0 dB, a result greater than any of the random samples in the dataset. This suggests the model was able to learn from the best of each configuration, and then produce even better, unseen designs.

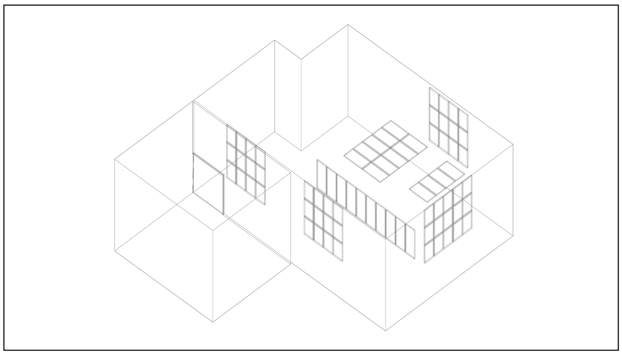

Figure 11. Panel configuration for increasing SNR generated by linear regression based method.

It is encouraging that the panel arrangement produced, Figure 11, looks very different to the previous T30 optimised configuration, suggesting that the model understands panels in different places have different benefits. For example, panel locations could be labelled as 'good for reducing T30' or 'good for increasing SNR'. Future work could investigate how to balance multiple objectives. Analysing the panel layout can reveal some possible explanations for why certain zones were considered more effective. A trivial observation is the inclusion of all the freestanding panels in the wall between the source-receiver pairs, blocking a lot of the direct path. Further insights can be gained using a visualisation to represent the direct path length from each of the sound sources. Using the right most sound source as an example, the free standing walls seem to cast a 'shadow' on the opposing wall, Figure 12. The linear regression appears to take this into account, and prefers panels on the upper half of the walls consistently, where they presumably absorb a larger portion of the direct sound path, reducing the signal reaching the opposing receiver. The ceiling panels were also determined to be as low as possible, and centred around the mid point of the source-receiver pairs, again presumably as these panels prevent a large amount of the first order ceiling reflections reaching the opposing receiver.

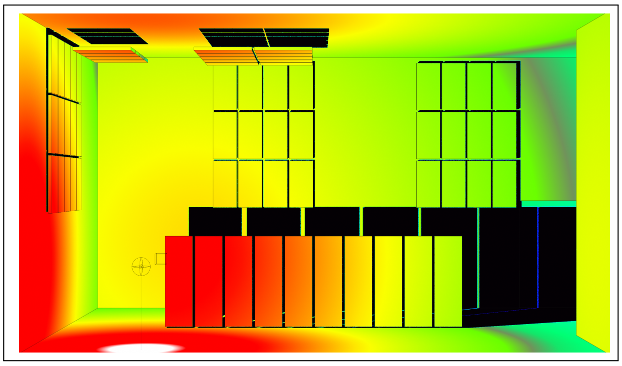

Figure 12. Source 1 direct ray visibility, with energy intensity approximation. Ceiling panels in raised position for visual clarity

5. CONCLUSION

5.1 Limitations

The method in this study exploited the ability to represent room parameters monotonically, i.e. increasing the number of panels in a zone is highly likely to decrease T30, making it possible to use coefficients to minimise or maximise each parameter. This may prove more challenging as the complexity grows and other variables are considered, for example furniture placement. Also, instead of the 'first past the post' approach taken to decide which parameters should be considered for implementation, a model which could balance all parameters may be able to create more nuanced and better performing solutions. To achieve this, the current method could be extended, for example to train a model, and then to feed the model many new and unseen random inputs to find the set of input parameters which achieve the best objective score. The false ceiling height parameter exposes another area of weakness, as this value changes the behaviour of the panels in these zones. This makes the performance of these zones more of an average over various ceiling heights, obscuring the performance of each zone at each ceiling height. Representing each zone at each ceiling height as a separate variable may improve model accuracy.

5.2 Outcomes

This study shows that the placement of acoustic panels in a space can significantly impact their effectiveness, and suggests that the placement of other acoustically significant objects may also make a difference to acoustic metrics, highlighting the potential gains in considering spatial variables in room treatment. This study also demonstrates it is possible to train a simple linear regression model on randomised panel configurations and simulated GA metrics. The linear regression model coefficients were used to create a configuration for reducing T30, which closely replicated best practices and recommendations. In a second scenario, the method produced configurations for increasing an SNR metric, which may have been difficult to arrive at analytically. This also demonstrates that with different objective measures, the method can create different and uniquely optimised configurations, provided the desired metrics are all simulated for each set of geometry. As long as the room configuration can be represented in a meaningful way, it is likely the optimisation techniques discussed will be able to design optimal configurations.

5.3 Future Work

To address the limitation of the coefficients only being able to minimise or maximise variables, other methods could be used, such as using gradient descent to find the variable values which give the minimum output of the model. More sophisticated approaches could also be used, such as modelling the room with a neural network, and then feeding in a large set of random configurations to identify those which are predicted to be the best performing.

With further research it may be possible to write more efficient, purpose driven acoustic simulations. For example, the results from the SNR experiment seem to suggest the most important factor for improving SNR was to maximise the area of the wavefront that was absorbed before the first bounce. If more evidence could be gathered to support observations like this, an acoustic ray tracer only concerned with low order rays could be written to very quickly approximate acoustic results for the specific purpose of optimising certain metrics. Advances like this could bring powerful acoustic optimisation into the hands of many more venues and buildings looking to improve their spaces.

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