

Training Teachers to Employ Design and Analysis of Computer Experiments for Research on Sustainable Building Design

Mrs. Laura Thomason, Mansfield ISD/The University of Texas at Arlington

Long time middle school teacher who is still on a quest to continue in my personal education. I participated in the RET project with UTA last summer and while I learned so much, the experience allowed me to impact my classroom teaching. Currently, I teach at Jerry Knight STEM Academy in Mansfield, TX. I get to teach advanced 6th, 7th, and 8th graders in multiple STEM electives.

Prof. Victoria C. P. Chen, The University of Texas at Arlington

Dr. Chen currently serves as Professor and Director of Doctoral Studies for Industrial, Manufacturing, & Systems Engineering and Director of the Center on Stochastic Modeling, Optimization, & Statistics at the University of Texas at Arlington. She has expertise in the design of experiments, statistical modeling, and data mining, particularly for computer experiments, adaptive dynamic programming, surrogate optimization, and stochastic optimization. She has studied applications in sustainability and energy, smart cities, transportation, health care, law enforcement, and chemical analysis.

Dr. Erick Jones, The University of Texas at Arlington

Erick Jones is an assistant professor in the IMSE department at UTA and the founder and director of the Sustainable and Equitable Allocation of Resources or SEAR Lab. He obtained a PhD from the Operations Research and Industrial Engineering program at the University of Texas at Austin, a B.S. in Chemical Engineering from Texas A&M University, and is a fellow of GEM, NSF INFEWS, and DOE MLEF. He spent several years working in the design, manufacturing, oil and gas, and HVAC industries. During this time, he traveled around the world and witnessed how the lack of basic infrastructure like electricity, HVAC systems, clean water, internet, and banking negatively affects the quality of life of the majority of life by improving access to sustainable resources and economic opportunities, particularly where a lack of physical infrastructure or economic resources presents a major obstacle, leading to the creation of the SEAR lab. The SEAR lab investigates how communities, companies, and countries can allocate their limited resources in a way that maximizes their desired outcomes in a sustainable, equitable, and resilient but also elegant way. The SEAR lab assesses these problems by combining physical experimentation, data analytics, and stochastic systems optimization to provide actionable decisions and create scalable prototypes.

Prof. Jay Michael Rosenberger, The University of Texas at Arlington

Jay Rosenberger is Professor and Interim Department Chair of Industrial, Manufacturing, & Systems Engineering. He is a past director for COSMOS and for the Center for Transportation Equity, Decisions & Dollars. He has expertise in mathematical programming, applied simulation, and optimization of statistical metamodels of complex systems. He has applied his methodological research to solve numerous real-world problems including those in transportation, health care, defense, and energy.

Jaivardhan Sood, The University of Texas at Arlington

Jaivardhan is a PhD student in the Industrial, Manufacturing, and Systems Engineering department at the University of Texas at Arlington. His research focuses on statistics, optimisation, and their intersection.

Vishnu Sharma Kaipu Prabhakar Sharma, The University of Texas at Arlington

Vishnu Sharma is a Graduate of the Masters of Data Science Program at the University of Texas at Arlington. His research focuses on Data Mining and Computer Experiments Analysis.

Soulmaz Rahman Mohammadpour, The University of Texas at Arlington



I am Soulmaz Rahman Mohammadpour, a second-year Ph.D. student at the University of Texas at Arlington, specializing in industrial engineering. With a background encompassing both Bachelor's and Master's degrees in the same (Industrial Engineering) field. Prior to my doctoral studies, I accumulated four years of practical experience in Supply Chain and Optimization roles at international companies like Unilever and Dairy Bel. With a combination of academic knowledge that I am developing in the University of Texas at Arlington under the supervision of Professor Jay Rosenberger and Professor Victoria Chen, and industry insight, I try to emerge as a promising scholar poised to make significant contributions to the field.

Rahsirearl Dominick Smalls, Everman ISD/The University of Texas at Arlington

Rahsirearl Smalls is an Early College Science Instructor at Everman Independent School District in Everman, TX. He was previously a Project Lead the Way teacher at Charles Baxter Junior High School when he participated in the RET project with UTA in the summer of 2022. This experience helped to shape the way he delivers STEM instruction to his students. His goal as an educator is to expose students to the various STEM careers that are available to them.

Mrs. Jocelyn Sigler M.Ed., The University of Texas at Arlington

With over 10 years of experience teaching HS/MS science, Jocelyn was an advanced biology and environmental systems teacher at Lamar High School in the Arlington Independent School District when she participated in the RET program in the summer of 2022.

James Hovey

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Abstract

The construction industry is one of the largest consumers of natural resources, including water, materials, and energy. Towards the goal of more sustainable building design, we present a "tiny home" case study that demonstrates our proposed design and analysis of computer experiments (DACE) process for conducting a comprehensive study of potential building designs. As part of a National Science Foundation Research Experiences for Teachers project (EEC-2055705), two cohorts of Junior High/High School teachers were trained to conduct the DACE process, employing sustainable building design software tools as computer models for the experiments. In this paper, we propose and illustrate the DACE process as a training framework for novice researchers who are brand new to research. The DACE process provides a general set of research tools, consisting of four steps: (1) Calibration of the computer model(s) for the application of interest, (2) Design of experiments to organize a set of computer model input parameter settings, (3) Execution of the computer model(s) to generate performance metric outputs, (4) Analysis of the input and output data. For sustainable building design, the performance metric outputs represent dimensions related to the pillars of sustainability: people, planet, prosperity. The first cohort of teachers focused on Steps 1-3, and the second cohort conducted Steps 2-4. This paper first provides a general description of the DACE process and articulates the engineering education connection with the Industrial Engineering undergraduate curriculum, then describes the teachers' implementation of the DACE process for the tiny home case study, as well as some of their thoughts on the program and project.

Introduction

Sustainability is defined by three pillars: people, planet, and prosperity. Green building design addresses sustainability from an energy efficiency perspective, which touches on all three pillars. Sustainable building design is an extension of green building that more directly considers the people and planet perspectives. Currently, buildings comprise 39% of U.S. energy consumption [1]. This motivated the project's main research question: What green building technologies are most important in achieving desired sustainability objectives? For our National Science Foundation Research Experience for Teachers (NSF RET) program we decided to tackle this research question. Teachers from local Junior High/High Schools participated in a sustainable retrofitting building design project in the Department of Industrial, Manufacturing, & Systems Engineering at the University of Texas at Arlington (UTA). For this project, the team studied three sustainability metrics: human health particulate (people), global warming potential (planet), and annual energy cost (prosperity). Teachers Jocelyn Sigler and Rahsirearl Smalls participated with the Summer 2022 cohort, and teachers Laura Thomason and James Hovey participated with the Summer 2023 cohort. They were guided by faculty mentors Drs. Victoria Chen and Erick Jones, Jr. and received research assistance from several IMSE graduate students.

To conduct the research to answer this research question, this paper proposes the adaptation of methods from the Industrial Engineering curriculum towards our proposed research training framework based on design and analysis of computer experiments (DACE [2-3]). A well-known research approach in science and engineering is the use of statistical design of experiments [4]. However, this approach requires expensive physical experimentation of different options, such as running laboratory experiments to study the effect of different chemical compounds or growing different varieties of crops in an agricultural setting. With the advent of computers, many systems can be modeled computationally based on existing foundational knowledge. Although some computer models are still considered computationally timeconsuming, they can explore different options in settings that would not be possible in physical experiments. Examples include photochemical air quality simulations and vehicle crash simulations. In the case of building design, there are existing computer models to help designers study the impact of their design without having to physically build it. For our NSF RET program, two software tools were employed: eQUEST (www.doe2.com/equest/), a building energy simulation program to simulate the amount of energy used by a designated structure, and Athena Impact Estimator for Buildings (ATHENA, www.athenasmi.org/our-software-data/impactestimator/), which assesses the life cycle of a building based on its materials and assemblies. Domain expertise in building design for calibrating the software tools was provided by Mr. Anthony Robinson, President of Axis Design-Build, Inc.

DACE [2-3] was introduced to efficiently leverage the availability of computer simulation models. For novice researchers that are brand new to research, the DACE approach provides a general research training framework because the domain expertise is predominantly contained within the computer model. DACE requires the research team to conduct the following steps:

- 1. Calibration of the computer model(s) for the application of interest.
- 2. Design experiments to organize a set of computer model input parameter settings.
- 3. Execution of the computer model(s) to generate performance metric outputs.
- 4. Analysis of the input and output data

The components of the DACE process are taught in standard Industrial Engineering (IE) undergraduate curricula. Steps 1 and 3 leverage content from a computer simulation modeling course. Step 2 uses an extension of design of experiments, typically introduced in the second statistics course, following an introductory course on probability and statistics. Finally, statistical modeling and operations research courses are useful for Step 4. Some more modern IE courses could introduce computer programming and machine learning that would benefit the entire DACE process. Consequently, an IE student could be easily introduced to research by employing the DACE process as a research training framework.

For our NSF RET sustainable building design project, teachers were novice researchers because K-12 educators do not normally get a chance to participate in research experiences. Our teachers worked with graduate students to execute eQUEST and ATHENA. They participated in the discussion on what building design options would be appropriate for retrofitting, such as upgrading windows or adding insulation. The experimental design was based on research by Dr. Chen and her graduated Ph.D. student, Dr. Shirish Rao [5]. A total of 48 computer runs were completed in Summer 2022, and an additional 32 runs were completed in Summer 2023. The

Summer 2022 teachers developed a plot of the three-sustainability metrics that enabled the identification of retrofitting building designs that most improved the metrics relative to the baseline, namely lower human health particulate, lower global warming potential, and lower annual energy cost. The Summer 2023 teachers utilized the combined data of 80 runs to conduct a regression tree analysis [9] to identify the building design options that were most influential on the sustainability metrics and to build a statistical model. The research team then discussed patterns identified by the analysis. One more cohort of teachers in Summer 2024 will participate in this NSF RET program.

NSF RET Background and Implementation

A primary goal of the NSF RET program is to encourage early engagement in research to strengthen the pipeline of domestically developed STEM research: <u>https://new.nsf.gov/funding/opportunities/research-experiences-teachers-engineering-computer</u>. The RET program seeks to achieve this goal by building relationships between university researchers and K-12 teachers, where a requirement of the RET program is the creation of lesson plans that teachers present in their classes, to stimulate students' interest in STEM research. Additional RET activities include student field trips to the university campus to visit research labs, writing and submission of research papers, and continued teacher involvement with subsequent teacher cohorts and future RET projects.

For UTA's implementation of their RET project, five project groups were studying different STEM topics led by different faculty groups and involving in a cohort of Junior High/High School educators who committed to a six-week period over the summer to work approximately 20 hours with the research teams from the University. The RET project lasts three years, corresponding to three sets of cohorts. For the group of educators working on the green building research question, the teachers began their research by running the computer models while still having the opportunity to ask questions of the graduate students and faculty mentors when needed. The entire team would gather for a few hours each week to discuss research progress, determine what is needed based on the previous week's work, and how to move forward in the project. This six-week period allowed the K-12 educators to see what it was like to be a part of a research team, which was a new experience for our teachers.

Outside of the research project, the RET participants also increased their own learning through webinars, campus tours, industry field trips, educational assessment activities, and interactions with everyone involved with the RET program. At the end of the six-weeks' time, the teachers completed a lesson plan incorporating aspects of what they learned and presented what they learned to a panel of stakeholders.

Over the next year, the teachers were encouraged to stay connected with the faculty mentors, and if they wanted to stay part of the research team, they were welcome to help where able. The teachers could help write research papers, attend conferences, or whatever could help advance the project. During the school year, teachers were observed twice as part of the assessment of the RET program. They taught the prepared lesson to students, and students completed surveys regarding their STEM understanding, one prior to the lesson and one after the lesson was completed. UTA also helped teachers provide engaging and interactive field trips for their students at no cost.

Methods

A typical use of computer models is "trial and error," which lacks a systematic method and misses critical model input parameter settings that are important to the study [2-3]. By contrast, the DACE approach [2-3] provides a general set of research tools for systematic exploration of computer models, described below in four steps:

1. Calibration of the computer model(s) for the application of interest.

Computer models are intended to study a range of model input parameters. Some of these parameters will be fixed to define the application of interest. Others will be selected to be varied in the study. The calibration step identifies which factors will be varied and then appropriately defines the fixed parameters. In the case of a building retrofitting application, the existing building design will specify certain fixed parameters, such as the number of floors, the building footprint, and the front-facing orientation. Some factors of interest that would be reasonable to modify in retrofitting could include upgrading windows, increasing insulation, adding a radiant barrier, and changing the exterior color of the building.

2. Design experiments to organize a set of computer model input parameter settings.

The concept of controlled experimentation is straightforward to describe to novice researchers with STEM interests. An experimental design is mathematically a matrix with columns that represent different factors of interest and rows that represent different experimental runs. For computer experiments, the factors are the input parameters of interest. These factors are systematically varied in the experimental design, and each row of the matrix sets each factor at a specific level. Given the specific settings of one row, a run of the computer model can be executed. Consider a portion of the matrix for an experimental design shown below in Table 1:

Table 1. Example excerpt of an experimental design.

	1 1	1	
Run	Factor 1	Factor 2	Factor 3
1	2	1	1
2	2	2	2
3	1	2	1
4	1	1	4
5	1	2	3
6	2	1	2
7	2	1	3
8	2	2	4

The first column indexes the rows of the matrix, and the first row indexes the factors. Factors 1 and 2 have two levels, identified simply as "1" and "2." These levels can represent any two levels of interest for a factor. For example, if Factor 1 specifies the presence or absence of a radiant barrier in a house, then "1" could be "radiant barrier present" and "2" could be "radiant barrier not present." Another example could be two types of water heating fuel, with "1" being "Electric" and "2" being "Gas." Factor 3 above has four levels, which could be selected from a larger set of possible levels. For example, insulation R-values have many levels, but a specific four R-values could be chosen to study.

For conducting computer experiments, experimental designs commonly employ methods based on orthogonal arrays, Latin hypercubes, or a Sobol' sequence [3]. A comprehensive compilation of orthogonal array based experimental designs is available from a web source maintained by Dr. Neil Sloane (neilsloane.com/oadir/ [6]). While orthogonal arrays are mathematically complex to derive, the resulting experimental design matrix has the same structure as the matrix in Table 1. Consequently, they are not complex for novice researchers to use. Latin hypercubes and Sobol' sequences are appropriate for factors that can be varied more continuously. In this case the experimental design matrix has values scaled between 0 and 1, and the research team would need to scale these to the range of the actual factors. For example, Table 2 has a portion of an experimental design matrix from a Sobol' sequence:

Table 2. Example excerpt of a continuously valued experimental design.

Run	Factor 1	Factor 2	Factor 3
1	0.234375	0.546875	0.515625
2	0.765625	0.703125	0.984375
3	0.421875	0.109375	0.203125
4	0.953125	0.296875	0.265625
5	0.296875	0.484375	0.640625

The basic structure is the same as Table 1, and the difference is that the factor levels are now values chosen continuously over the range from 0 to 1. Suppose Factor 1 is a budget limit on the cost of building construction, then this can be continuously varied over a desired range. If this range is from \$100,000 to \$500,000, then the scaling would map "0" to \$100,000 and "1" to \$500,000, and the value 0.234375 for Factor 1 in Run 1 would map to a budget limit of \$193,750, using the scaling formula:

 $(fraction) \times (range) + minimum = (0.234375) \times (500,000 - 100,000) + 100,000 = 193,750.$ Latin hypercubes and Sobol' sequences can be generated using existing software tools, such as the *lhsdesign* and *sobolset* functions in Matlab (www.mathworks.com).

3. Execution of the computer model(s) to generate performance metric outputs.

This step is ultimately the data collection step. The computer model's runs are executed following experimental design, where each run will correspond to output from the computer model. The research team will have identified which output values are key performance metrics for the study. Depending on the study, there could be multiple performance metrics. For sustainability applications, all three pillars should be represented by the set of performance metrics.

4. Analysis of the input and output data.

Once the data have been collected, various analyses can be conducted to explore patterns relating to the input parameters of interest with the chosen performance metrics. In the case of two or three performance metrics, it is useful to generate a plot of the performance metric values, one on each axis, where three metrics would require a 3D plot. This plot allows the research team to view which runs achieved the "best" solutions. If we assume that smaller is better for all metrics, then a run that achieves a point closest to the origin in all dimensions would be a clear winner. However, in most multiple metric cases, there are conflicting objectives, where improving one could lead to degradation in another. In Figure 1, the data for two performance metrics are

plotted, where it is desired to minimize both metrics. If there were a solution at the orange point, then this would be a clear winner. However, it is noted that this is "infeasible," meaning that it is not an actual solution. Among the actual data points, the "best" solutions lie on the Pareto frontier [7]. These are closest to the origin, but there is not a clear winner that is minimized in both performance metrics.

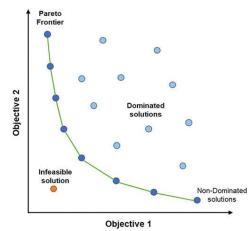


Figure 1. Plot of data for two performance metrics (Objective 1 and Objective 2) with non-dominated solutions lying on the Pareto frontier [8].

To study the relationship between the factors (model input parameters of interest) and the performance metrics, various statistical modeling methods can be employed, including treebased models, regression-based models, and machine learning models [3]. For novice researchers, a regression tree-based model [9] is flexible and provides output that is easily interpretable.

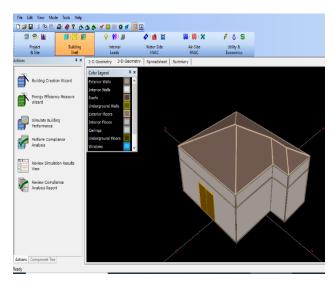
Sustainable Building Design Case Study

Over the last two years, two cohorts of public-school educators have worked with UTA through the NSF RED grant EEC-2055705. This grant involves multiple projects conducting sustainability research in IE, Civil Engineering, Electrical Engineering, and Physics. The IE project specifically studies sustainable building design using the DACE process. The case study in this paper addresses a UTA tiny home research project led by the School of Architecture. The tiny home design is being used for a micro-community housing development called Wynn Terrace in Arlington, TX. Retrofitting options recommended by our NSF RET project are under consideration for this micro-community. During the summer of 2022, the cohort of Smalls and Sigler focused on Steps 1-3 of the DACE process. Blueprints for the tiny home were provided by Architecture Professor Charles MacBride (see Figure 2). During the summer of 2023, the cohort of Thomason and Hovey continued with Steps 2-4, including more computer experiments.



Figure 2. Blueprint drawing from UTA School of Architecture tiny home project.

For Step 1 of the DACE process, Smalls and Sigler spent several weeks calibrating the computer models in the software tools eQUEST and ATHENA based on the blueprints. Most of the building design specifications were set in eQUEST, and then output from eQUEST provided input to ATHENA. Performance metrics *human health particulate* and *global warming potential* are measured by ATHENA, while *annual energy cost* is measured by eQUEST. Figures 3 and 4 provide screenshots of the eQUEST and ATHENA software tools:



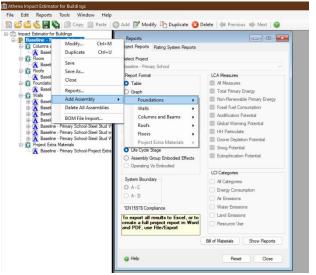


Figure 3. Screenshot of eQUEST software tool user interface.

Figure 4. Screenshot of ATHENA software tool user interface.

The building design specifications in the blueprints provided the Baseline settings for the tiny home case study. The retrofitting perspective of the case study was to identify if alternative "easy to modify" building design options could yield improvements in sustainability. For retrofitting, Table 3 lists 18 building design options that were identified and the settings that were studied.

Building Design Options (Factors)	Model Input Parameter (Factor) Levels	
HVAC: Heating Source	DX Coils, Electric Resistance	
HVAC: Supply Fans	Variable, Forward Curved Centrifugal w/ Inlet	
	Vanes	
Heater Specifications: Heater Type	Tank Storage, Instantaneous	
Heater Specifications: Heater Fuel	Electric, Natural Gas	
Roof: Ext Finish/Color	Uncolored, Light Color, Dark Color, Aluminum Paint	
Roof: Exterior Insulation	Continuous Range from None to R-42	
Roof: Additional Insulation	Continuous Range from None to R-60	
Roof: Radiant Barrier Option	No Radiant Barrier, Yes Radiant Barrier	
Above Grade Walls: Ext	Uncolored, Light Color, Medium Color, Dark	
Finish/Color	Color	
Above Grade Walls: Exterior		
Insulation	Continuous Range from None to R-21	
Above Grade Walls: Interior		
Insulation	Continuous Range from None to R-7	
Above Grade Walls: Add'l Insulation	Continuous Range from None to R-21	
Ceilings: Batt Insulation	Continuous Range from None to R-30	
Vertical Walls: Batt Insulation	Continuous Range from None to R-60	
Windows: Glass Category	Single Low E, Double Low E,	
	Triple Low E Film, Quadruple Low E Film	
Windows: Glass Thickness	1/8-inch, 1/4-inch	
Windows: Glass Spacing and Gas	1/4-inch Air, 1/3-inch Krypton, 1/2-inch Air	
Windows: Frame Type	Aluminum, Reinforced Vinyl, Wood, Fiberglass	

 Table 3. Retrofitting building design options (model input parameters) and factor levels studied for the tiny home case study.

For Step 2 of the DACE process, two experimental designs were employed, one for each cohort of teachers. For the Summer 2022 cohort, it was decided to first study only two levels for each factor, knowing that the following year's cohort could extend the study with more levels.

From the Sloane website, under "Two levels and strength 3," the orthogonal array labeled "oa.48.24.2.3.2" was selected. This label's notation can be translated as 48 runs, up to 24 factors, with 2 levels per factor, and strength 3 orthogonal array structure [3]. The website lists 60 orthogonal arrays with these same numbers, so the last number in the label indicates the second array of the 60. In Summer 2023, as a preliminary Step 4 of the DACE process, a regression tree analysis [9] using R software (https://www.r-project.org/) was conducted on the 48 runs from Summer 2022. This analysis identified one level as clearly superior for each of the first four factors in Table 3, specifically, DX Coils for Heating Source, Forward Curved Centrifugal with Inlet Vanes for Supply Fans, Tank Storage for Water Heater Type, and Electric for Water Heater Fuel. Consequently, for the Summer 2023 experimental design, these four factors were fixed, and the remaining 14 factors were varied, with 7 continuous over specified ranges and 7 discrete with specified levels.

The Summer 2023 design did require a level of sophistication, so the selected experimental design was a Kung Sliced Latin Hypercube [5], which creates a hybrid of a mixed orthogonal array and a sliced Latin hypercube. The orthogonal array is used to represent the 7 discrete factors, and the sliced Latin hypercube is used to represent the 7 continuous factors. A Latin hypercube selects unique values uniformly over the continuous range: if there are 32 runs, then a continuous factor will have 32 distinct values. For the discrete factors, not all levels in Table 3 were studied within one experimental design. To limit the number of computer model runs to be manageable within the time of the six-week summer workshop, two levels were studied in Summer 2022, and other levels were studied in Summer 2023. Specifically, for the

second experimental design, Glass Category was represented by all 4 levels in Table 3, but the other 6 discrete factors were represented by 2 levels. The number of runs for this design is determined by the orthogonal array. In this case, the R package *DoE.base* was used to identify an experimental design with 32 runs, up to 9 factors with 2 levels, up to 5 factors with 4 levels, and one possible factor with 8 levels. In summary, Step 2 of the DACE process yielded a total of 48+32 = 80 runs. Each run specified a retrofitting building design for the tiny home. It should be noted that an experimental design that studied all the combinations of the studied levels in Table 3 would require this calculation for the number of runs:

 $2^7 \times 3^1 \times 4^3 \times 32^7 > 8.4 \times 10^{14}$ runs

This is over 100 trillion runs. Hence, it can be observed that the generated experimental designs from the DACE process are far more efficient in terms of the number of runs.

As an initial part of Step 4 of the DACE process, the Summer 2022 research team generated Figure 5 to illustrate the estimated Pareto frontier [7-8] using their 48 retrofitting building designs. The red points are building designs that define the estimated Pareto frontier (green triangle). The green point is the tiny home baseline building design from the blueprints. The first *research finding* was uncovering that there were retrofitting building designs that could yield improvement in the sustainability performance metrics. In particular, the DACE process with only 48 computer model runs, was able to uncover this finding and motivate further research for the tiny home design.

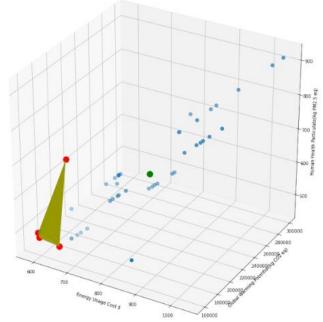


Figure 5. 3D plot of the 3 sustainability performance metrics: human health particulate (vertical), global warming potential (right), annual energy cost (left).

Combining the 48 runs from Summer 2022 and the 32 runs from Summer 2023, the research team conducted regression tree analysis [9] for Step 4 of the DACE process. Figures 6-7 show the results for human health particulate; Figure 8-9 are for global warming potential; and Figure 10-11 are for annual energy cost. Figures 6, 8, and 10 provide the relative variable importance measure, where the top-ranked factor is scaled to an importance of 100. Figures 7, 9, and 11 provide the fitted tree model diagram. Lower values of the performance metric follow the

left branch of each split. Since it is desired to minimize our three sustainability performance metrics, the factor levels on the left branches of the splits are the preferred levels, so for Figures 7 and 9, only the left side of the tree diagram is shown. In general, important factors should appear in the tree diagram, but this is not universally true because a factor variable could be important on its own, but in the presence of other factor variables, could be less important.

The tree models for the two sustainability performance metrics human health particulate and global warming potential identify similar research findings. While the tree models in Figures 7 and 9 are not identical, they both identify the following factor levels as leading to better performance: DX Coils for Heating Source, Natural Gas for Water Heater Fuel, non-Wood Window Frame Type, Aluminum Paint or Uncolored Roof Exterior Finish, and lower Insulation R-values. The tree model in Figure 11 is more compact than the other two tree models, indicating that modeling annual energy cost is more straightforward than the other two metrics. However, the factor levels that achieve lower annual energy cost are consistent with the other two metrics: DX Coils for Heating Source, Natural Gas for Water Heater Fuel, and Aluminum Paint or Uncolored Roof Exterior Finish. The Heating Source result is consistent with what was observed using solely the Summer 2022 data, but the Water Heater Fuel result is the opposite; however, Natural Gas is considered to be a more sustainable fossil fuel.

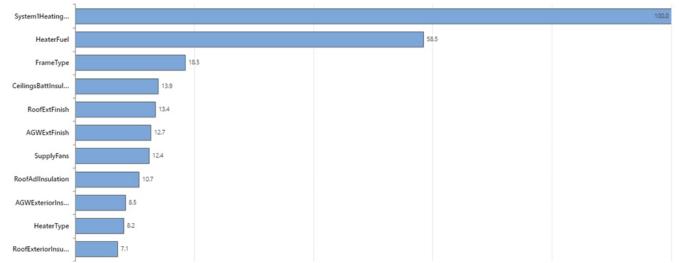


Figure 6. Relative variable importance for the sustainability metric human health particulate.

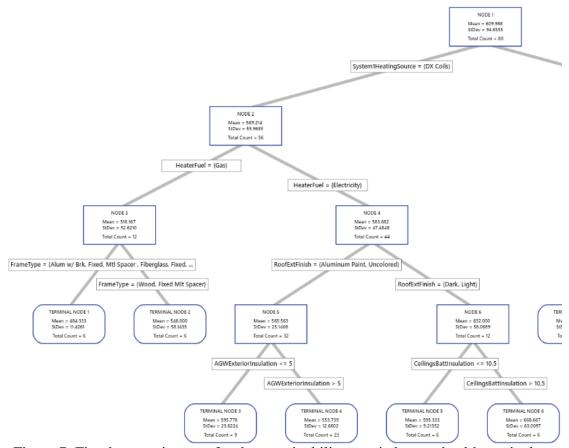


Figure 7. Fitted regression tree for the sustainability metric human health particulate.

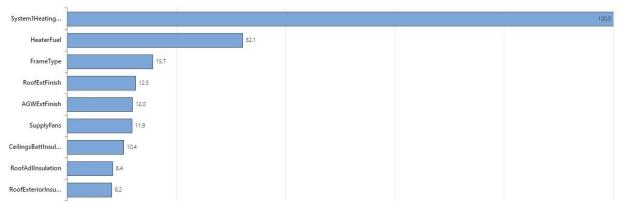


Figure 8. Relative variable importance for the sustainability metric global warming potential.

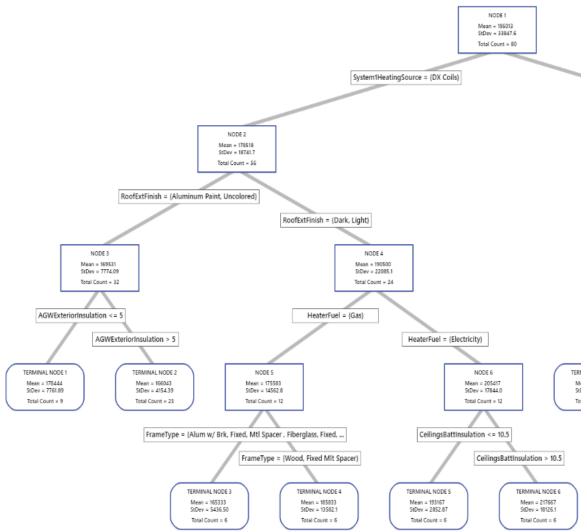


Figure 9. Fitted regression tree for the sustainability metric global warming potential.

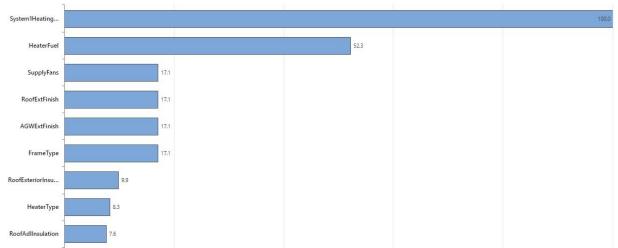


Figure 10. Relative variable importance for the sustainability metric annual energy cost.

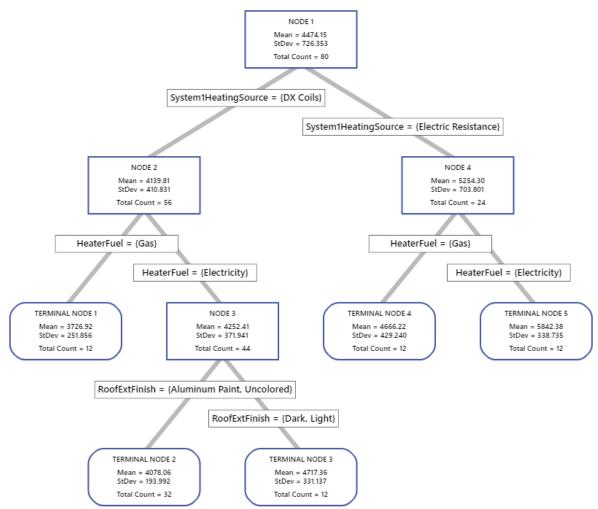


Figure 11. Fitted regression tree for the sustainability metric annual energy cost.

The identification of Aluminum Paint or Uncolored Roof Exterior Finish as being more sustainable is consistent with the tiny home baseline building design. Also, the recommendation to avoid Wood Window Frame Types is potentially consistent with views of unsustainable deforestation. The recommendation to use lower Insulation R-values was considered counter to green building practices since higher insulation should lower energy consumption. However, it is reasonable to conclude that the materials employed for insulation have a potentially negative impact on human health and the environment. Finally, it seemed odd that the Window factors Glass Category and Thickness did not appear in any of the tree models. Further research will seek to explore this.

Finally, the Summer 2023 cohort of teachers also learned about a computer-aided design (CAD) program called SketchUp to help visualize the tiny home design. UTA graduate student Vishnu Sharma provided training on how to use the program, and then each of the educators worked to create a 3D rendering of the tiny home in SketchUp, shown in Figure 12. After using the CAD software, Thomason created a 3D-print at UTA's library. The library staff explained the process of taking the created STL file and converting it to a GCODE file to be printed. Some iterations were needed to enable a successful 3D-print.



Figure 12. Thomason's SketchUp rendering of the tiny home.

Implementation in K-12 Classroom

From the Summer 2022 cohort, Smalls had his Junior High School students participate in a tiny home building challenge focusing on the Engineering Design Process. The lesson began by looking at the three pillars of sustainability and comparing them with environmentally friendly perspectives. This was a great start to help the students understand how they are similar but also different. Afterward, they discussed the tiny home craze that is spreading in home construction and then worked in groups to create an environmentally friendly tiny home design while staying on budget. This lesson allowed Smalls the opportunity to incorporate his learning about sustainability into his classroom while providing his students with a hands-on learning experience that was relevant to the real world.

From the Summer 2023 cohort, Thomason and Hovey had the idea of having students in two different districts and two different age groups work together to show collaboration and

sharing of knowledge within the community. Thomason's lesson plan for Junior High School learners in her Project Lead the Way Green Architecture class included utilizing eQUEST software to run simulations focused on one building material and fixed insulation R-values. After obtaining the simulation results, the plan is to share them with Hovey's students in his Engineering class. Hovey's class would then utilize regression trees [9] in R software and plot Pareto frontiers [7-8] to analyze the results.

While the Summer 2023 cohort has not yet implemented this lesson as originally envisioned, Thomason's 8th grade learners did complete a project-based learning unit using skills from the NSF RET experience and her understanding of the DACE process. The students learned and discussed the three pillars of sustainability while using the Engineering Design Process to research, plan, test, analyze, and present their results. The eQUEST software tool was used by all learners to determine how different insulations impacted the energy consumption (kWh) of the tiny home. They then incorporated math by researching the cost of the insulation used and the energy cost for the initial year, 5 years, and 10 years of ownership. Her learners then analyzed their results and completed a written analysis report over their findings utilizing what they learned in their English Language Arts class regarding technical writing. The results of their cross-curricular learning were then presented to their peers. At a Junior High School STEM campus, letting learners experience a real-world problem and using industry equipment to investigate and analyze results is extremely important. This project allowed her students to test out several types of insulation available and see that the R-values did not impact the overall energy usage enough to push for the higher R-value product. This went against what they hypothesized and expected from their research on insulation. Without the NSF RET project, Thomason would not have known how to accomplish this type of lesson with her learners or have the confidence to pursue this with them.

This year, Hovey incorporated many portions of his learning this past summer into his High School Engineering classes. He utilized the "burrito optimization game" from Gurobi (https://www.gurobi.com/burrito-optimization-game/) to start a conversation about why optimization is important since it is impossible to try every combination when testing. He also shared regression trees with some of his upper classmen and split the class into groups that pulled large public datasets and used Python coding to create their own regression trees. While degrees of success varied, he felt that the students understood the overall concept. Hovey has also partnered with some of the graduate students and Ph.D. students from UTA's College of Engineering to help his students with some projects and competitions. His students really appreciated the UTA students taking the time to help his high schoolers understand how engineering is impactful in the real-world.

Concluding Remarks

The experience educators gain from being a part of the NSF RET project has shown to be more impactful than any other professional development. Smalls has not only increased his knowledge and understanding of how different building decisions affect energy use, emissions, and cost but has been able to share Engineering with a more meaningful impact for his students than before. In the spring of 2023, he was able to take 50 students to see UTA's College of Engineering, so that the Junior High School students could see all the different majors and careers available in the field. Participation in the RET project allowed Thomason, a lifelong educator, a chance to participate in a research-driven problem in an Engineering field. What she gained provided her with real-world experiences that resulted in real-world learning that impacted not only her earners but also all the learners she will teach in the future. The six-week intensive program put her directly into the research team and allowed her to be a part of the process. She experienced challenges and problems while working with the team, but she also persevered and had successes and triumphs. Throughout the entire program, growth as an educator was happening in her that will continue to trickle down and make her a better educator for years to come.

Hovey expressed how his knowledge of Engineering broadened. His participation has positively impacted his classroom directly in the way he approaches making his lessons. He tries to incorporate real world topics as much as possible and now he also tries to bring Engineering into as many assignments as possible. Hovey expressed that his RET experience with UTA also allows for him to better advocate for Engineering majors and feels comfortable discussing Engineering more broadly with students and has many top students considering attending UTA for Engineering degrees.