

**S10-6****ENERGY EFFICIENT BUILDING DESIGN THROUGH DATA MINING APPROACH****Hyunjoo Kim<sup>1</sup> and Wooyoung Kim<sup>2</sup>**<sup>1</sup> Researcher, USA Corps of Engineers, Engineering Research and Development Center<sup>2</sup> Research Fellow, CERIK(Construction & Economy Research Institute of Korea), Seoul, Korea.Correspond to [beladomo@cerik.re.kr](mailto:beladomo@cerik.re.kr)

**ABSTRACT:** The objective of this research is to develop a knowledge discovery framework which can help project teams discover useful patterns to improve energy efficient building design. This paper utilizes the technology of data mining to automatically extract concepts, interrelationships and patterns of interest from a large dataset. By applying data mining technology to the analysis of energy efficient building designs one can identify valid, useful, and previously unknown patterns of energy simulation modeling.

*Keywords: Energy Simulation; Data Mining; Classification*

**1. INTRODUCTION**

Building energy simulation programs have been developed, enhanced, and are in use throughout the building energy community. The energy modeling programs provide users with key building performance indicators such as thermal loads, energy use and demand, temperature, humidity, and costs. The A/E/C industry is embracing energy simulation programs, so building designers are currently dealing with a large amount of data generated during energy simulations. From our experience, even a simple run of energy modeling generated several pages of data with many different variables. Examples of those variables include but are not limited to the estimated energy costs in terms of orientation of a building, HVAC system, lighting efficiency and control, construction of roof and walls, glazing type, water usage, day-lighting, etc. Such volumes of data clearly overwhelm the traditional methods of data analysis such as spreadsheets and ad-hoc queries with many factors to be considered and it is difficult to find the best correlation/combination of different energy systems in a building design process.

The objective of this research is to develop a knowledge discovery framework which can help project teams discover useful patterns to improve energy efficient building design. This paper utilizes the technology of data mining, which is a data analysis process that combines different techniques from machine learning, pattern recognition, statistics, and visualization, to automatically extract concepts, interrelationships and patterns of interest from a large dataset. By applying data mining technology to the analysis of energy efficient building designs one can identify valid, useful, and previously unknown patterns of energy simulation modeling.

This paper presents the necessary steps to develop the

data mining approach such as 1) problem identification, 2) data preparation, 3) data mining, and 4) data analysis.

In order to establish a framework, a case study was conducted with an on-going design project. Then detailed steps and tools of energy analysis in early design are presented in a framework.

**2. Literature Review****2.1 Energy Modeling**

For the past 50 years, a wide variety of building energy simulation (BES) analysis tools have been developed, enhanced, and applied throughout the building energy community. Examples of these tools are BLAST, EnergyPlus, eQUEST, TRACE, DOE2, and ECOTECT. Input data in these tools are complex, 2D drawing or text-based applications which require a great deal of time to learn [1]. Building designers consider energy analysis a time-consuming process and leave it to mechanical or electrical engineers late in the design process. Several research papers describe energy analysis as a holistic evaluation [2]. Dahl et al. [3] and Lam et al. [4] showed that decisions made early in a project have a strong affect on the life cycle costs of a building. As Grobler [5] presented in Figure 1, building designs (conceptual and detailed designs) affect most of the life cycle costs of the construction and operation of a building. A recent innovation in building design and construction, Building Information Modeling (BIM) has received tremendous interest for its impact on sustainable development and provides the opportunity to develop energy analysis software programs for the industry. It is also worth noting that several researchers proposed to combine Lean and BIM technologies to improve modeling process in sustainable development [6]. While the converging

approach would enable virtual simulation in collaborative environments, and thus is expected to change the A/E/C industry in terms of delivery and management of the built environment, it is found that the approach emphasizes the whole process in design and construction processes. Yezioro et al. [7] conducted assessing building performance using 3D CAD model for energy analysis in the early design stages.

## 2.2 Data Mining Implementation for Pattern Discovery

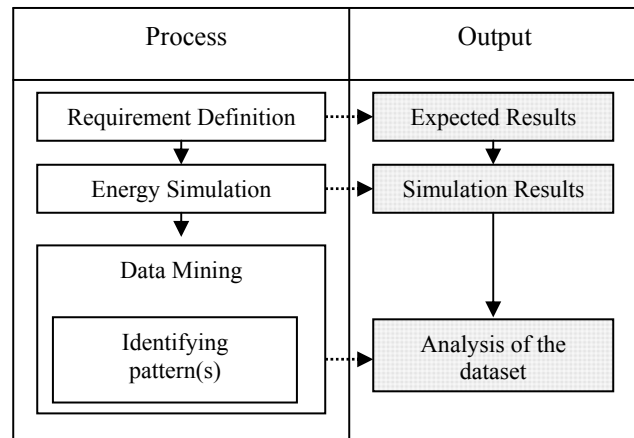
Historically, the notion of finding useful patterns in raw data has been given various names, including knowledge extraction, information discovery, information harvesting, data archeology, and data pattern processing [8]. By the end of the 1980s, a new term, KDD, was coined to replace all of the old terms referring to methods of finding patterns and similarities in raw data. Artificial intelligence and machine learning practitioners quickly adopted KDD and used it to cover the overall process of extracting knowledge from databases. KDD can be considered an interdisciplinary field involving concepts from machine learning, database technology, statistics, mathematics, high-performance computing, and visualization. Although the main concern of database technologists has been to find efficient ways of storing, retrieving, and manipulating data, the machine learning and statistical community has been focused on developing techniques for learning knowledge from data. The visualization community, on the other hand, has been concerned with the interface between humans and electronically stored data. The complexity of the mining algorithms and the size of the data being mined make high performance computing an essential ingredient of successful and time-critical data mining. Fayyad et al. [9] define KDD as the nontrivial process of identifying valid, novel, potentially useful, and ultimately understandable patterns in data. John [10] defines it as the process of discovering advantageous patterns in data. Because the use of automated methods distinguishes KDD from any traditional methods of data analysis, the authors of this paper define KDD as the partially automated process of finding potentially valid, useful, and previously unknown patterns from large data sets.

A pattern is an expression of describing facts in a subset of a set of facts. The expression is called a pattern if it is simpler than the enumeration of all facts in the subset of facts. In this research, the novel pattern means that construction managers may manage their construction projects more efficiently in terms of schedule/cost management, etc. through the patterns found.

## 3. CASE STUDY

In this section, a sequence of four different steps in the data mining process is outlined, as shown in Figure 1. The first step is to identify the project requirements. This may present several challenges as many projects have constrained budgets, schedules, and resources. It is essential that all building stakeholders--including owners, designers, engineers and contractors--have a clear understanding of problem definition and participate in

identifying a set of design alternatives early in the project planning process. The second step, energy simulation, is where you generate a large amount of data. From our experience, even a simple run of energy modeling generated several pages of data with many different variables. Examples of those variables include estimated energy costs in terms of orientation of a building, HVAC system, lighting efficiency and control, construction of roof and walls, glazing type, etc. Such volumes of data clearly overwhelm the traditional methods of data analysis such as spreadsheets and ad-hoc queries with many factors to be considered and it is difficult to find the best correlation/combination of different energy systems in a building design process. The third step is data mining process where we develop an overall data analysis mechanism that can be applied to find patterns that explain or predict any behaviors in the energy simulation.



**Figure 1.** Main Process of Knowledge Discovery Approach

### Requirement Definition

The project described in this paper is a new Community Emergency Service Station (CESS) facility. This building will provide fire fighting, medical and police support services for a residential neighborhood. The station consists of offices, training rooms, physical training, day room, kitchen, dormitory area, apparatus room, decontamination room, storage area/rooms, latrines, communication and electrical closets, and a mechanical room. The size of the proposed new facility is approximately 8,300 SF. The apparatus room was sized for a fire truck, military police car, and ambulance. Space for hose drying, lockers and a work bench were also required in the apparatus room.

Identification of requirements for the CESS facility was accomplished using the charrette process. A charrette is held at the beginning of a project where a group of designers, engineers, and contractors may draft solutions to design problems. For our case study, the charrette took place in the early stage of design and also included stakeholders outside of the design/build team. Each

participant presented his/her work to the full group. The charrette served as a way of quickly generating solutions while understanding and integrating the interests of different groups of people. The outcome of the charrette was a 35% complete integrated building design.

Energy modeling in the case study presented several challenges. First, it was essential to provide energy analysis results so we could identify energy-saving improvements while the design was being modified. In addition, energy modeling usually involves the time-consuming process of re-entering all the building data for an energy analysis.

**Energy Simulation**

While there are several different BIM-based energy modeling software programs available, Green Building Studio (GBS) was specifically chosen to generate energy-related estimation. The goal of this research was to use the building geometry and details contained in a BIM model to quickly build an energy analysis model to compare energy-related tradeoffs early in design. More than just the lines and arcs associated with traditional computer-assisted drawing (CAD) tools, BIM includes associated benefits of visualization, built-in intelligence and simulation, intelligent objects of a structure, such as spatial data (3D), unstructured data (text), and structured data (databases, spreadsheets), as shown in Figure 2. With the addition of building geometry data in a BIM model, the volume can be calculated and energy estimates made based on building envelope characteristics (doors and windows) and building orientation.

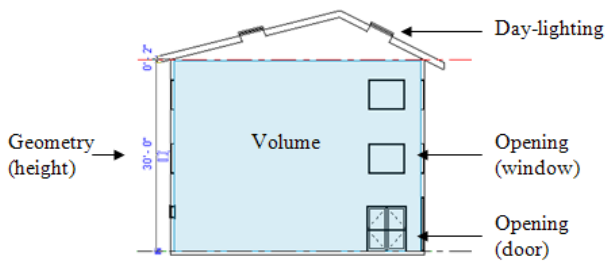


Figure 2. 3D-CAD/BIM model

**Data Analysis**

- HVAC
  - The range of estimated energy cost is between \$2,710 and \$336.
  - The best option is with 17 SEER/0.85 AFUF Split/Pkgd<5.5 ton.
  - In overall, SEERs are more efficient than Pipe Fan Coil System.
  - More efficient HVAC equipment will be found for additional savings.

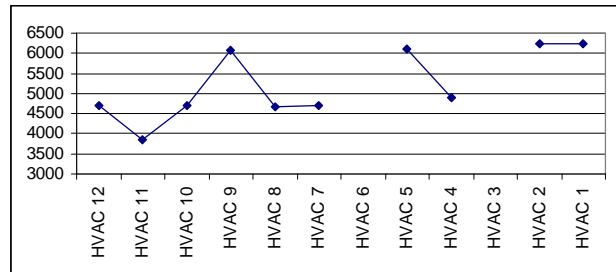


Figure 3. HVAC Energy Modeling

- Rotation
  - The best option is to have the longest wall face the south.
  - The worst option is turning the building 90 degrees clockwise at the additional cost of \$11.
  - Each option is not significant in its cost difference with the range of \$0 to \$11.

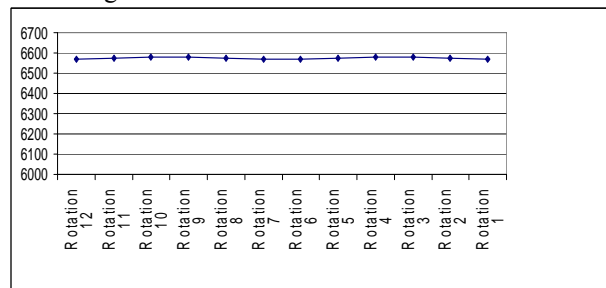


Figure 4. Rotation Energy Modeling

- Lighting Power Density (LPD)
  - The range of savings is within \$232 and \$59.
  - Average Lighting Power Density was 1.55 W/ft2.

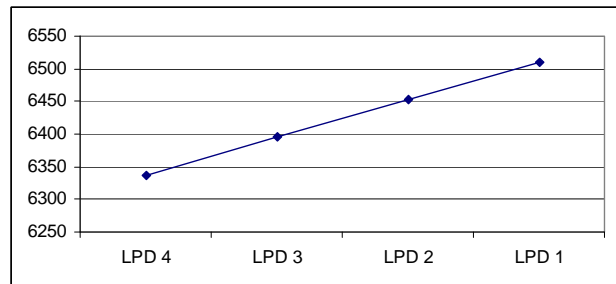


Figure 5. LPD Energy Modeling

- Roof Construction
  - The range of savings from roof construction is between \$47 and \$-143.
  - The best option is with either Wood Frame Roof with Super High Insulation or Metal Frame Roof with Super High Insulation (\$47).
  - The worst is from Cool Roof – R15continuous insulation over roof deck (\$-143).
  - Increasing R values with Cool Roof didn't turn out to be good alternatives.
  - No difference is found between wood frame roof and metal frame roof.

- Wood or metal frame is better than Continuous Deck Roof, Cool Roof-R15 continuous insulation over roof deck or structural insulation.
- Increasing R value in Cool Roof continuous insulation over roof deck produced good results.

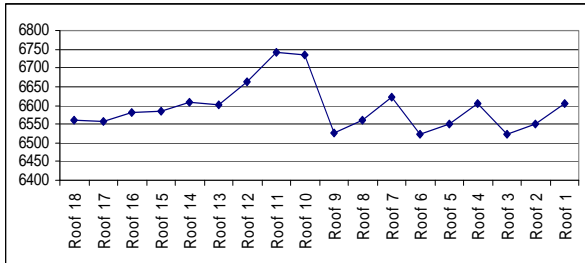


Figure 6. Roof construction Energy Modeling

- Variance
  - o The greatest variance is with Cool Roof-R15 continuous insulation over roof deck.
  - o The least variance is found with Structural Insulation Panel (SIP) roof.
- More efficient HVAC equipment will be found for additional savings.

- Roof Glazing

- The range of the savings is between \$7 and \$-1.
- The best option is from Insulated Clear Low-E Cold Climate.
- The worst choice is from Insulated Reflective (\$-1).
- Green or bronze is a little superior to blue or grey (about \$5)
- Insulated Low-E is better than reflective or translucent.
- Monolithic Clear Low-E is a good choice in roof glazing.
- Clear glazing was the highest while reflective was the lowest in performance.

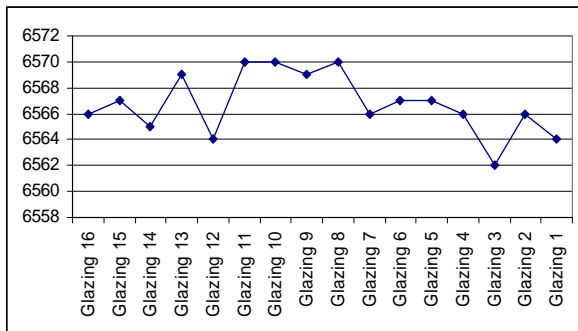


Figure 7. Roof glazing Energy Modeling

- North Wall Construction

- The best option came from the Wood Frame Wall with Super High Insulation (\$148).
- The worst was from Massive Wall (or metal frame) with Code Compliant Insulation (\$-18).
- The best alternatives are either Structural Insulation or Insulated Concrete Form(ICF).
- Unlike roof, there is difference between wood frame and metal frame.

- Variance
  - o High with Massive Wall
  - o Low with Structural Insulated Panel (SIP) Wall or Insulated Concrete Form (ICF) Wall.

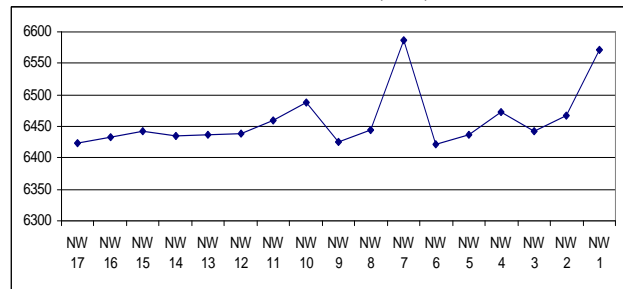


Figure 8. North Wall Energy Modeling

- North Wall Glazing

- The range of energy cost is between \$34 and \$8.
- The best option is to choose Translucent Wall Panel (U-.10, SHGC-0.06, Tvis-0.04).
- The worst is to choose Translucent Wall Panel (U-0.53, SHGC-0.36, Tvis-0.25).
- Variance
  - o High with Translucent Wall Panels
  - o Low with Insulated Low-E

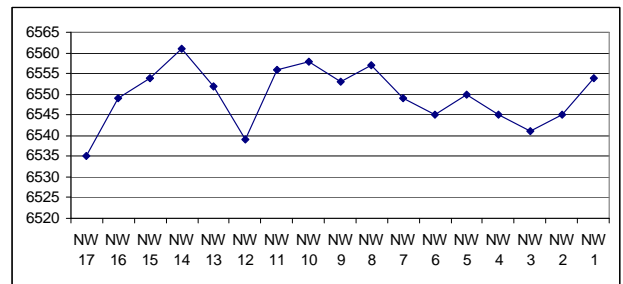


Figure 9. North Wall Glazing Energy Modeling

**Summary**

Comparison of annual energy costs for each design alternative was conducted in the six categories (10 different options in HVAC, 17 in glazing, 20 in roof, 15 in walls, 4 in lighting, and 3 in lighting control) of building elements. The comparison in Figure 10 shows that different building elements result affected the energy estimations. Compared to the baseline building performance, HVAC options had the greatest impact on annual energy costs, with estimated \$1,507 saving using a 17 SEER/0.85 AFUE Split/Pkgd. On the other hand, lighting controls had the least impact on energy costs: \$11-17/year.

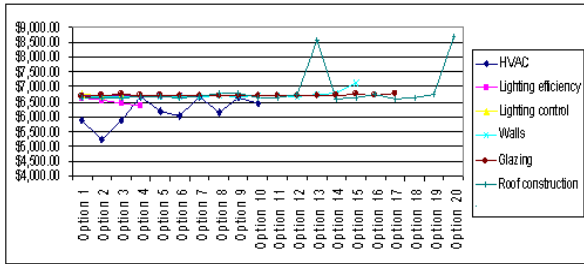


Figure 10. Comparison of different energy estimation

- Annual energy cost for base case model is estimated at \$6,569.
- Location: Fort Lewis, WA
- Floor Area: 3,967 ft<sup>2</sup>
- Number of people: 167
- Six areas have been measured.
  - Orientation
  - HVAC
  - LPD
  - Roof
  - Wall construction (north, south, east, west walls)
  - Window glazing
- Impacting factors are in the order of:
  - HVAC (\$2,710)
  - Wall construction (\$397) \*North wall (\$148)
  - Windows (about \$100) \*South wall windows (\$55)
  - Roof construction (\$47)
  - Roof glazing (\$7)
  - Orientation (\$-11)

#### 4. CONCLUSIONS

Utilizing data mining-based energy modeling technology, this research conducted an energy modeling process where project teams may utilize energy simulations and see the results early in the design process. To date, energy modeling tasks are usually left to mechanical or electrical engineers due to its time consuming data entry and occur late in the design process. The case study revealed that data mining based energy modeling help project teams discover useful patterns to improve energy efficient building design.

The process conducted by this research could be used to guide designers and engineers through the process of completing an early design energy analysis based on energy simulation models.

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