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MULTI-OBJECTIVE BUILDING ENERGY SYSTEM OPTIMIZATION CONSIDERING EV INFRASTRUCTURE

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ABSTRACT

With increasing concern related to carbon dioxide emission, concept of Zero Energy Building (ZEB) appears. Electric Vehicles are also considered environment friendly automobiles to reduce greenhouse gas emission. With global trends above, Building energy system should consider ZEB concept and electricity demand for EVs charging. Therefore, this thesis suggests reasonable problem-solving method to find the best optimal energy system design to meet ZEB condition. EVs charging demand is predicted from the fittest Machine Learning regression model. This result combined with Hourly Building Energy demand from EnergyPlus simulator. Last Genetic Algorithm and PROBID method will be applied to meet two objective functions : Annual Total Cost and Self-Energy Sufficiency ratio.

Keywords: Renewable energy, energy system optimization, NSGA2, Zero Energy Building, Electric Vehicle, Energyplus

NONMENCLATURE

Abbreviations	
AC	Absorption Chiller
E	Energy
EHP	Electric Heat Pump
ESS	Energy Storage System
EV	Electric Vehicle
FC	Fuel Cost
GC	Grid Cost
GHP	Gas Heat Pump
HY	Fuel Cell
MC	Maintenance Cost
MCDM	Multi-Criteria Decision Making
NG	Natural Gas
nZEB	nearly Zero Energy Building
NZEB	Net Zero Energy Building
PV	Photovoltaic
SSR	Self Energy Sufficiency Ratio
ZEB	Zero Energy Building
ZEB Ready	Zero Energy Building Ready
Symbols	
ele	Electricity
h	hour

1. INTRODUCTION

Nowadays One of the serious environmental issues in the world is ‘Greenhouse gas emission’. Especially, Building accounts for 33% of the world’s greenhouse gas emissions [1]. With rapid urbanization, more buildings will be built and more energy will be consumed. And it leads the green house gas emission issue that is fatal to human existence is going to be even more serious. Therefore, many countries put a lot of efforts to solve Greenhouse gas emission problem. In 21st Conference of the Parties (COP-21) held in Paris in December, 2015. In this conference 195 countries and EU agreed that ‘holding the increase in the global average temperature to well below 2°C’ [2]. For achieving the above global agreement, it becomes important to design a building that consumes less energy, and improve the energy efficiency of buildings with the use of renewable energy.

With this trend Companies or individuals in many countries are required to build Zero Energy Building (ZEB). Due to limited technology and a high cost, constructing ZEBs is not an easy task for developing countries. Therefore, the definition of ZEB differs in many countries to alleviate the negative impacts on society. These are the four main definitions of ZEB based on how much energy building can produce per year : ZEB Ready, nZEB, NZEB and Plus Energy building. In

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conclusion, ZEB buildings are defined according to each country's policy. And ZEB will be designed to maximize energy efficiency using a variety of renewable energy sources.

Considering both self-sufficiency ratio and cost, this research proposes an optimal energy system design to achieve ZEB condition. Furthermore, problem-solving methods described in the research can be applied to the design of an energy system for ZEB. A multi-objective optimal design of an energy system will be created in the research using building simulation programs and mathematical programming methods. The proposed method can be used as a decision-making tool and as a guide for optimizing ZEB in general.

2. METHODOLOGY

2.1 Building Energy demand prediction model

Major Building Energy Demand consists of 3 energy demands: electricity, heating and cooling. Due to the increasing number of electric vehicles, the presence of EV charging stations in buildings has become increasingly important. Thus, EV charging should be taken into account when a building's energy system is designed. Charging demand for EVs derived from a prediction model will be combined with electricity demand for building. Figure 1 shows the overview of the method for predicting building energy demand.

Fig. 1. Method for pedicting building energy demand

2.1.1 EV charging demand prediction model

In this research the best ML prediction model will be selected based on value of errors (MSE, RMSE, MAE) to predict electricity charging demands in Buildings.

To find the best regression model, 5 regression ML models are tested : MLR(Multi-Linear-Regression), ANN(Artificial Neural Network), Bagging ANN, GBM(Gradient Boosting Machine) and RF (Random Forest) regression model.

2.1.2 Energy demand simulation using EnergyPlus

Building energy simulation software, EnergyPlus, is developed by the United States government. Energy consumption patterns in buildings vary depending on their type. So, 16 prototypes of building can be used in EnergyPlus. Passive technology which is one of the characteristics of ZEB will be fixed with the use of prototype buildings. Therefore, it makes the optimization of active technologies in the building so called energy system more convenient.

After simulation, hour scale 1year energy demand can be calculated. It should be modified with using actual data. Accordingly, monthly based demand data will be used in conjunction with EnergyPlus simulation results to represent reality. To do so, EnergyPlus benchmark models [3] will be applied to change monthly energy demand to hourly energy demand.

2.2 Energy System modelling for nZEB

The energy system in the building is broken down into various technologies and mathematically modeled. And each technology is combined again based on the types of energy demand.

2.2.1 Energy technology selection

Prior to modelling an energy system, energy technologies for buildings are selected based on the weather and government policies. In this research, energy technologies are selected based on Korean Government policy and the most prominent energy technologies in Korea. Korea's government supports gas cooling systems in order to reduce electricity power peaking during summer.

In this research EHP, boiler and GHP are selected for heating demand. And EHP, absorption chiller and GHP are selected for cooling demand based on Korean situation. Those selected energy technologies can be changed in other countries or locations according to their policy or geographic location.

2.2.2 Modeling method

Each technology is modeled independently under constraints. After modelling, each of the technologies is again combined using energy balance equations. Generally, energy balance equations are divided into three energies, such as electricity, heating, and cooling. For this research, we will take into account EV infrastructure, so charging demand for EVs will be added to the electricity energy balance equation. Those are the characteristics of the energy balance equations used in this study : Hourly Scale, EV infra and Modelling technologies separately

2.2.3 Energy system constraints

Various alternative energy conversion technologies are modelled independently, and then unified deployment is carried out through the constraint equations of material and energy balance of each energy flow in the integrated energy system, e.g., cooling, heating and electricity constraint[4]. Figure 2 shows Energy System in the building.

Building and EV charging electricity demand is met by PV panels, ESS, fuel cells (natural gas based) and imported power from the grid. The heating demand is met by EHP, GHP, boilers, and heat storage. The last cooling demand is satisfied by EHP, GHP, and absorption chillers. Equations below show the balance of electricity, heating and cooling. Equation1 shows energy balance equations. (Electricity, Heating and Cooling respectively)

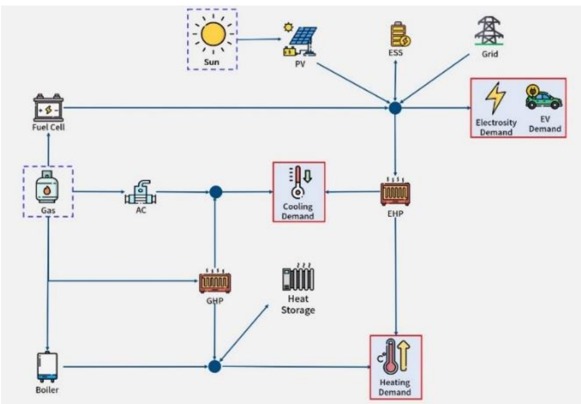


Fig. 2. Energy System for the case study

$$E_h^{ele} + E_h^{EV} = E_h^{PV} + E_h^{HY} + E_h^{ESS\_dis} - E_h^{ESS\_cha} - 0.1 \times NG_{\mathrm{h}}^{\mathrm{ghp\_c}} - 0.09 \times NG_{\mathrm{h}}^{\mathrm{ghp\_}h}$$

$$- 0.2 \times ele_{\mathrm{h}}^{\mathrm{ehp\_c}} - 0.05 \times ele_{\mathrm{h}}^{\mathrm{ehp\_}h} + E_h^{grid}$$

$$Q_h^{heat} = Q_h^{ehp} + Q_h^{ghp} + Q_h^{Boiler} - 0.95 \times \mathrm{NG}_{\mathrm{h}}^{\mathrm{ac}} + Q_h^{heat\_dis} - Q_h^{heat\_cha}$$

$$E_h^{cool} = E_h^{ehp} + E_h^{ghp} + \mathrm{E}_{\mathrm{h}}^{\mathrm{cool\_ac}}$$

Equ. 1. Energy Balance Equations

2.3 Multi-objective Optimization

2.3.1 Objective Function

In order to meet criteria of nZEB, Buildings must produce at least 20% of a year's energy consumption on their own. As part of the eight technologies discussed in Chapter 2.2.1, solar, fuel cells, ESS, EHP, GHP, and heat storage are considered renewable energy technologies. Table 1. shows category of each technology.

Table 1. Category of each technology

Energy Source	Technology
Renewable energy	Solar, FC, ESS, EHP, GHP, HS
Energy	Boiler, Absorption Chiller, grid

As one of the objective functions, the quantity of renewable energy produced in the building is divided by the quantity of energy demand in the building. It is called the Self-Energy Sufficiency Ratio (SSR). In this study, one of the objective functions is set to meet level 5 ZEB which has at least 20 percent SSR annual basis. The Primary Energy Factor (PEF) is required to calculate SSR. In Korea, the value of PEFs is 2.75 for electricity and 1.1 for natural gas. SSR will be calculated based on these values.

The economic factor is also a very important element when it comes to building an energy system. Economic factor is generally calculated as Annual Total Cost (ATC). ATC consists of capital expenditure (CAPEX) and operating expense (OPEX). CAPEX is the capital cost of all technologies in the building. OPEX is the operating cost of all technologies in the building energy system. It includes maintenance cost (MC), fuel cost (FC) and grid cost (GC). Equation2 shows SSR, ATC objective functions respectively. Objective functions are Minimizing ATC and Maximizing SSR at the same time.

$$\mathit{Minimize}\ \mathrm{ATC} = \mathrm{CAPEX} + \mathrm{OPEX}$$

$$\mathit{Maximize}\ \mathrm{SSR} = \sum_h (E_h^{PV} + E_h^{HY} + E_h^{ESS\_dis} + Q_h^{ehp} + Q_h^{ghp} + Q_h^{heat\_dis}\ E_h^{ehp} + E_h^{ghp})$$

$$/ \sum\left(\frac{Monthly\ Energy\ bills}{8760}\right)$$

Equ. 2. Objective Functions

2.3.2 NSGA-II for MOO and PROBID for MCDM

Proposed by Deb et al. (2002)[5], Non-dominated Sorting Genetic Algorithm II (NSGA-II) has been one of the most popular algorithms in solving multi-objective optimization (MOO) problems to obtain many uniformly distributed optimal solutions, which are equally good from the perspective of the given objectives, and hence also known as non-dominated solutions or Pareto-optimal solutions (after the Italian economist, Vilfredo F.D. Pareto). A set of Pareto-optimal solutions are obtained after solving multi-objective optimization (MOO) problem. However, ultimately only one solution has to be chosen from the set of Pareto-optimal solutions for implementation (Wang et al., 2020)[6]. In the present study, PROBID method (Wang et al., 2021)[7] is utilized to recommend one solution from the Pareto-optimal front because of its proven ranking consistency and robustness.

3. CASE STUDY

3.1 Data collection and preprocessing

The Large hotel in Je-ju island, South Korea is selected for the case study. EV charging data sets received from Korean Government, Week or Weekend, Number of EVs, Number of PHEVs and Temperature will be used for regression model. Table2. shows error of each regression model.

Table 2. Error of each regression model

Location	Regression Model	Error		
		MSE	RMSE	MAE
Office	MLR	223.31	14.94	9.93
	ANN	129.71	11.39	7.57
	BaggingANN	130.18	11.40	7.30
	GBM	163.11	12.77	7.79
	RF	**120.20**	**10.96**	**6.90**
Residential	MLR	40.33	6.35	5.11
	ANN	30.20	5.50	4.27
	BaggingANN	**29.42**	**5.42**	4.21
	GBM	30.74	5.54	4.30
	RF	29.87	5.47	**4.20**

The best models are Random Forest and Bagging ANN. However, there are no significant differences. Therefore, Random Forest is selected to predict EV charging demand in the building at both sites.

3.2 Case Study : Energy simulation using EnergyPlus

Table 3. Peak Energy demand

Peak Energy	Date	Energy Consumption(kWh)			
		Electricity	EV	Heating	Cooling
Electricity (office)	8pm 2nd Sep	**2303**	**78**	7	558
Electricity (residence)	8pm 2nd Sep	**2303**	**41**	7	558
Heating	4am 22nd Jan	522	32	**563**	209
Cooling	7pm 14th Aug	1910	129	0	**751**

After using simulation using Energyplus, Peak Energy demand can be calculated. Table3 shows peak energy demand. Each peak energy will be used to optimize capacity of Energy system.

3.3 Multi-objective Optimization

After applying GA, Figure3 shows result of GA algorithm for optimizing capacity of each energy technologies at office area and residence area respectively. There is not huge difference between the office and residence areas. Table4 shows the result of energy system capacity after applying GA.

Table 4. Result of Energy system Capacity (Unit : kWh)

Technology	Solar(m^2)	ESS	Boiler	HS	FC	AC	GHP	EHP	Grid
Capacity(kWh)_office	20.17	111.59	33.85	149.80	0.01	291.28	619.28	174.24	2301
Capacity(kWh)_residence	89.04	148.85	109.11	40.17	0.01	261.39	752.22	176.35	2233

Final ATC is 918,624 and 956,596 USD without subsidy. It can be reduced to 906,223 and 942,592 USD respectively after applying subsidy.

4. CONCLUSION

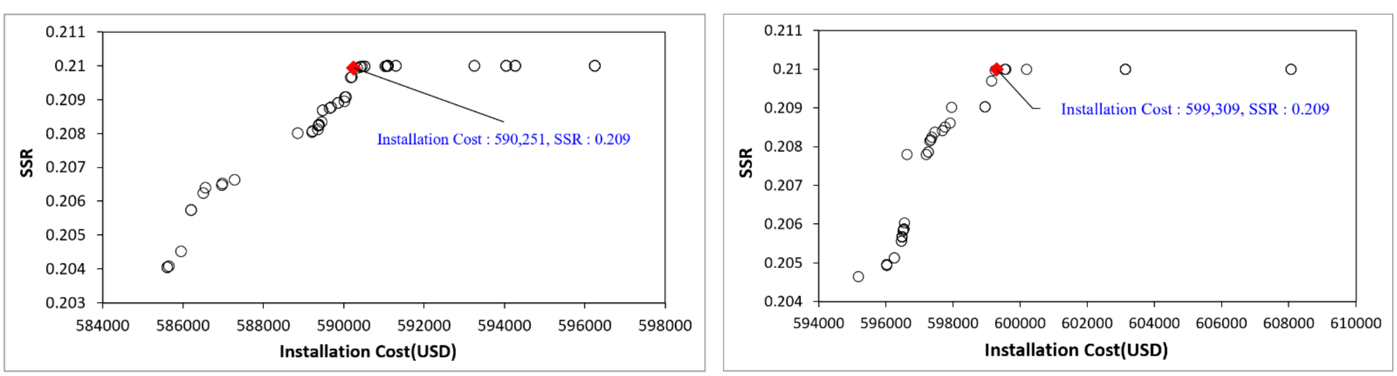
ZEB buildings have many benefits. As a short-term perspective, building owners have the opportunity to receive subsidies from the government and tax benefits. From a long-term perspective, ZEB buildings can alleviate the problem of global greenhouse gas emissions. With regard to the charging demand for EV, this research focuses on optimizing energy system capacity in order to meet nZEB criteria. The main conclusions are as follows:

(1) In this study, energy systems for buildings are chosen based on the policies of the Korean government. Korean criteria is also selected as the objective function. Modelling an energy system or defining the ZEB can be applied in different ways, depending on the situations.

(2) In this study, EV charging demand is considered using machine learning. The best ML regression model with the lowest error value is selected to predict the charging demand for electric vehicles.

(3) The Energyplus is used to predict the hourly energy consumption of a building. Because hourly energy demand data cannot easily be obtained, this study used the energyplus benchmark model[3] to predict hourly energy demand. Thus, it makes easier and faster for researchers to get a reasonable energy demand.

Figure 3. Result of GA algorithm : Pareto Frontier



(4) In this study, the NSGA2 algorithm was applied, a powerful algorithm for solving multi-objective problems. There are two objectives: Economic factor, ATC, and Environmental factor, SSR. After obtaining the Pareto-Frontier, PROBID will be applied to obtain the best solution. With NSGA2 and PROBID, decision makers can find the optimal solution while considering both economics and the environment without falling into local optimality.

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