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Development of an integrated multi-objective optimization model for determining the optimal solar incentive design

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Summary

To promote the deployment of the solar PV system from the long-term perspective, the solar photovoltaic (PV) industry in many countries still needs the financial support from the government despite its remarkable growth and price reductions in the last decade. Many countries with this financial burden on their government budget, however, are planning to reduce or to expire the financial support step by step. To bring the solar PV market to its full maturity, it is crucial to improve the solar policies and to sustain the financial support with acceptable and reasonable prices, which can maximize the benefits for the investors while minimizing the incentive budget for the government. Towards this end, this study aimed to develop an integrated multi-objective optimization (iMOO) model for determining the optimal solar incentive design from the perspectives of the investor and the government. A Microsoft-Excel-based iMOO model was developed using life cycle cost (LCC) analysis, genetic algorithm (GA), and Pareto optimal solutions. The developed Microsoft-Excel-based iMOO model was applied to six target regions to verify its effectiveness in determining the optimal solar incentive design. As a result, it was shown that depending on the various characteristics (e.g., solar radiation, electricity price, installation cost) of a region, the optimal solar incentive design can be differently determined with a reasonable and acceptable level using the developed iMOO model. Among the six target regions, Newark required the lowest incentive budget of US\$10,648.41 whereas Oklahoma City required the highest incentive budget of US\$20,648.73 to offer their optimal solar incentives. The model developed in this study can help both the investor and the government in a decision making process and provide some solutions and insights for planning solar policies and strategies.

Keywords: *Solar policies; State solar incentives; Solar photovoltaic system; Multi-objective optimization; Genetic algorithm; Life Cycle Cost (LCC)*

1. INTRODUCTION

To cope with global crises such as climate change, and to reduce the greenhouse gas (GHG) emissions, many countries are implementing various policies and incentives that can promote renewable energy [1-3]. In particular, the solar photovoltaic (PV) market has shown remarkable growth thanks to its great potential and the government support for the last decade [4-6]. Furthermore, the continuous growth of the solar PV technology led to the price reduction of the solar PV system, allowing some leading countries, such as Germany, to reach solar grid parity, where the price for generating electricity from solar energy becomes less than or equal to the electricity price from the conventional power plants (i.e., fossil fuel and nuclear energy) [7-11]. Even with the market growth and price reduction, the solar PV market in many countries, even in Germany, still relies on the government support, which was the key success factor for the growth of the solar PV industry [7, 12-14]. Moreover, some regions still lack solar policies and incentives even with high solar potentials that can bring success to their solar PV industry [15]. Therefore, it is necessary for the government to financially support the solar PV market to promote the deployment of the solar PV system from the long-term perspective [16-17].

As the global solar PV market becomes mature, countries with financial burden on their government budget are planning to reduce or even to expire the different forms of government financial support, such as solar subsidies and incentives, step by step [18-19]. Especially, various types of solar incentives have been largely phased out in the United States (U.S.) despite of high initial investment cost of the solar PV system compared to other international markets [9]. For instance, the federal investment tax credit (FITC), one of the strongest solar incentives in the U.S., was previously scheduled to be discontinued at the end of 2016. However, Congress passed a spending bill in December, 2015 which includes a five-year extension of the FITC for the solar PV system, until 2022, due to the potential risk of rapid solar PV market decline. Specifically, the FITC will remain the same at 30% of the initial investment cost until

2019, and will continuously decline to 26, 22, and 10% by 2020, 2021, and 2022, respectively [4, 20]. As shown in this case, it is necessary to improve the solar policies and to sustain the financial support with acceptable and reasonable prices, which can maximize the benefits for the investors while minimizing the incentive budget for the government to bring the solar PV industry to its full maturity.

When making a decision regarding solar policies and incentives, especially in the U.S., it is also crucial to consider the key factors affecting the technical and economic performance of the solar PV system, such as solar radiation and electricity prices. This is because these key factors, which vary widely by state, can bring different financial returns by state. Thus, these key factors should be also considered for determining the optimal solar incentive design, which can differentiate the optimal types and levels of the solar incentive depending on the region in the U.S.

Previous studies were conducted to analyze and investigate solar policies and incentives according to various purposes (refer to Table I) [21-48]. First, several previous studies evaluated solar policies and incentives through financial analysis [21-28]. Janko et al. [21] explored financial aspects of residential ratepayers and electric utilities by analyzing the combined effect of electric rate structures and local environmental forcings (i.e., net metering) on the optimal residential solar PV system size in three regions in the U.S. Swift [22] compared the cost and financial returns of commercial solar PV systems in four regions in the U.S. with different solar radiation, electricity prices, and solar incentives, using the levelized cost of electricity. These previous studies, however, mainly focused on the financial analysis of the current solar policies and incentives and failed to suggest specific solar incentive levels and strategies by region.

Second, some previous studies evaluated solar policies and incentives through impact analysis [29-40]. Coffman et al. [29] evaluated the solar PV tax credit policy in Hawaii with

the payback period (PP) and internal rate of return in terms of the investment benefits, income distribution, and taxpayers. Comello and Reichelstein [30] evaluated an alternative phase-down scenario of FITC, different from the current scenario, which is scheduled to step down from 30 to 10%. These previous studies, however, considered only certain types of solar policies or incentives for evaluation, and failed to suggest an overall solar incentive design and reasonable incentive levels in a specific region.

Third, other studies optimized the solar incentives from various perspectives of the stakeholders [41-46]. Kim and Lee [41] developed a model that can evaluate and optimize the FIT from a policymaker's perspective for increasing the renewable energy supply while keeping the total burden on the ratepayers. Das and Cañizares [42] proposed an optimal incentive design for minimizing the total system cost and incentive payments for the government while maximizing the profits for the generation company. Chen and Song [43] proposed an optimal subsidy level for maximizing both the net policy benefits (i.e., the difference between energy conservation and the subsidy cost) for the government and the investor benefits. These previous studies considered various perspectives of the stakeholders through multi-objective optimization, but this was not sufficient to fully consider various optimization objectives and to solve their complicated trade-off problems. Moreover, the previous studies on this issue often tended to focus on the budgetary decisions of the government, among those of the various other stakeholders, which often leads to minimum investor profit. Overall, there were few studies that developed a decision support tool for determining the optimal solar incentive design, despite the difficulty and necessity of establishing an acceptable and reasonable standard for financial support.

In summary, several previous studies analyzed solar policies and incentives from various points of view, but they still could not overcome the following limitations: (i) there were limited studies that considered various types and levels of solar incentives for determining the optimal

solar incentive design; (ii) there were limited studies that considered various perspectives of the stakeholders by solving the trade-off problem between the investor benefits and the government budget through multi-objective optimization; and (iii) there were limited studies that developed a decision support tool for determining the optimal solar incentive design. To address this challenge, Lee et al. [47] conducted an economic and environmental assessment of the residential solar PV system in all the 50 states and the District of Columbia in the U.S., considering various key factors, including solar radiation, electricity prices, and state solar incentives. It could not suggest any solution, however, for differentiating the solar incentive designs by state. As a follow-up study, Lee et al. [48] quantified the cash incentive rates that could satisfy the two target threshold performance levels (i.e., “net present value (NPV)=US\$0” and “PP=10 years”) for 16 incentive scenarios in the U.S. However, it was able to suggest only 16 representative scenarios with representative solar incentive values (i.e., maximum value, most likely value, and minimum value) as solar incentive strategies in each target region.

Therefore, this study aimed to develop an integrated multi-objective optimization (iMOO) model for determining the optimal solar incentive design which can maximize the benefits for the investors while minimizing the incentive budget for the government. From the perspectives of the investors, they would prefer high solar incentives from the government which can maximize their benefits and minimize their initial investment costs. From the perspectives of the governments, they would prefer to offer low solar incentives per installation due to the limited incentive budget, however, they still need to encourage and promote the installation of the solar PV system. In this respect, the developed iMOO model mainly focuses on these economic aspects of two stakeholders, both the investors (including residents) and government, and more specifically, the trade-off relationships between the investor benefits and the government budget. Towards this end, the iMOO model was developed in the following procedure: (i) step 1: establishment of a database; (ii) step 2: generation of incentive scenarios;

(iii) step 3: calculation of the electricity generation; (iii) step 4: life cycle cost (LCC) analysis; (v) step 5: multi-objective optimization using a genetic algorithm (GA) and Pareto optimal solutions; and (vi) step 6: Microsoft-Excel-based iMOO model development (refer to Fig. 1). The model application was also conducted for six target regions to verify the effectiveness of the developed Microsoft-Excel-based iMOO model for determining the optimal solar incentive design.

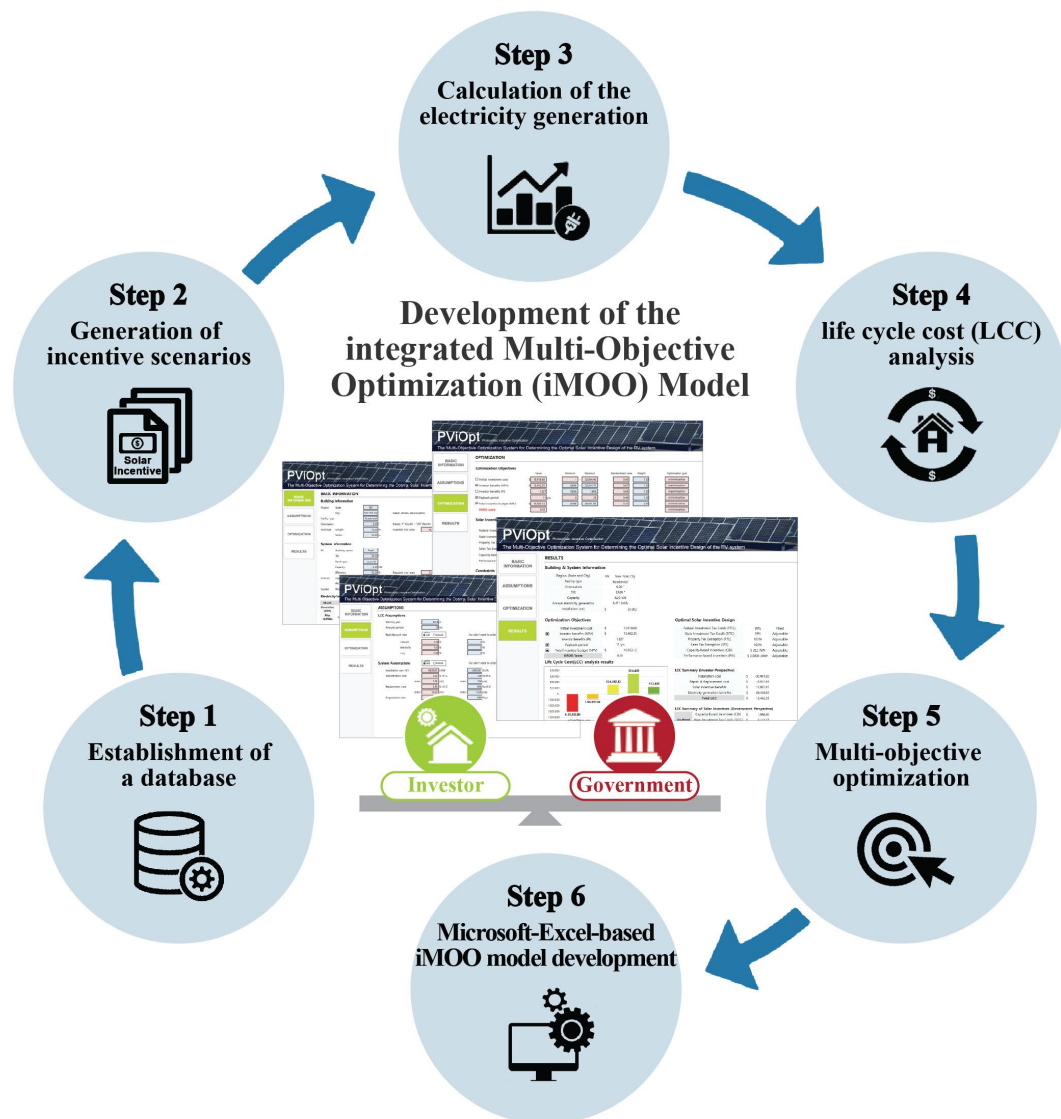


Figure 1. Research framework

2. MATERIALS AND METHOD

2.1. Step 1: Establishment of a database

To develop the iMOO model, this study established a database required for determining the optimal solar incentive design by state in the U.S. As this information varies by state, the database was established according to the regional difference. First, the key factors affecting the technical performance of the solar PV system were collected. The energy generation of the solar PV system can differ according to these key factors, which vary by state.

- The meteorological information, such as the solar radiation and air temperature, was collected from the weather data provided by *RETScreen*, a clean-energy management software used for calculating the electricity which can be generated from the solar PV system. *RETScreen* provides weather data such as solar radiation and air temperature in various regions across the world.

Second, the key factors affecting the economic performance of the solar PV system were collected. The economic feasibility of the solar PV system can differ according to these key factors, which vary by state.

- The electricity price was collected from the U.S. Energy Information Administration (EIA) [49]. U.S. EIA, the statistical and analytical agency within the U.S. Department of Energy, provides various energy information, including energy production, stocks, demand, imports, exports, and prices. The average retail price of electricity in 2015 by state and sector (i.e., the residential, commercial, and industrial sectors) was used because various electric utilities supply electricity at different prices by service area and sector in the U.S.
- The installation cost was collected from *The Open PV Project* [50]. *The Open PV Project*, developed and operated by National Renewable Energy Laboratory, provides a comprehensive database of solar PV installations in the U.S. established by the

government, industry, and public. This study used the average installed costs of the solar PV system by state and capacity (i.e., under 10 kW, 10-100 kW, and over 100 kW) from 2014 to 2015 because the solar PV system is installed at different unit prices by region and capacity in the U.S.

2.2. Step 2: Generation of incentive scenarios

To consider innumerable incentive scenarios during the optimization process, this study defined three types of parameters that can affect the technical and economic performance of the solar PV system. First, the defined parameters decide the variables to be fixed during the optimization process. The building and system information were selected as defined parameters. The building information includes the region, facility type, and orientation, and the system information includes the tracking option, tilt angle, panel type, installed capacity, and efficiency.

Second, the constraint parameters restrict the number of incentive scenarios by selecting the scenarios to be excluded from all the possible scenarios. The cash incentive budget was selected as a constraint parameter so that only the practical and reasonable incentive scenarios would be considered during the optimization process.

Third, the adjustable parameters generate innumerable incentive scenarios by combining different types of solar incentives. From the state solar incentives currently being offered in the U.S., a total of six types of solar incentives (four types of tax incentives and two types of cash incentives) were selected as adjustable parameters: (i) tax incentives such as the investment tax credit (i.e., the FITC and state investment tax credit (SITC)) and tax exemption (i.e., property tax exemption (PTE) and sales tax exemption (STE)); and (ii) cash incentives such as capacity-based incentives (CBI) and performance-based incentives (PBI).

- *Investment tax credit*: The government supports a certain percentage of the installation cost of the solar PV system. The FITC is being offered by the federal government, and

the SITC is being offered by the state government.

- *Tax exemption:* The government does not impose a property or sales tax on the installation of the solar PV system. The PTE exempts a person from paying the property tax imposed on the increased home value due to the installation of the solar PV system, and the STE exempts a person from paying the sales tax on the installation cost of the solar PV system.
- *Cash incentives:* The government or electric utilities offer rebates or incentives for installing the solar PV system. CBI is offered once in advance depending on the installed capacity of the solar PV system, and PBI is offered annually depending on the electricity generation of the solar PV system in that year.

Table II shows sample values and units for the six different solar incentives used as the adjustable variables in this study [51-52]. By combining these six solar incentives with different rates, it is possible to generate a large number of incentive scenarios, which can highly affect the economic feasibility of the solar PV system.

2.3. Step 3: Calculation of the electricity generation

To evaluate the technical performance of the solar PV system, this study used *RETScreen* to calculate the electricity generation of different solar PV installation scenarios. *RETScreen*, a clean-energy management software, enables the simulation of various renewable energy systems [53-55]. The meteorological, building, and system information are required to calculate the electricity generation for each solar PV installation scenario using *RETScreen*. First, the meteorological information, such as the solar radiation and air temperature, should be entered as input data. When the user selects the region (i.e., state and city), the weather data of the corresponding region provided by *RETScreen* is directly used as the input data, as mentioned in step 1. Second, the building information, such as the orientation, should be

entered as input data. Third, the system information, such as the tracking option, tilt, panel type, capacity, and efficiency of the solar PV system, should be entered as input data.

2.4. Step 4: LCC analysis

To evaluate the economic performance of the solar PV system, this study used the present-worth method to calculate the LCC of different incentive scenarios. The LCC analysis results of the solar PV system can be presented in terms of two different perspectives: (i) that of the investor; and (ii) that of the government. First, the LCC analysis results from the perspective of the investor are presented in various different financial indices, such as NPV, profitability index (PI), and PP, to evaluate the investment value of the solar PV system and to calculate the investor benefits. Expressed in Eqs. (1) and (2), NPV and PI respectively represent the sum and ratio of the cash inflows and outflows. When NPV exceeds “US\$0” and PI exceeds “1”, it can be considered that the minimum investment value of the solar PV system is guaranteed, and its economic feasibility has been achieved. PP makes it simple for investors to evaluate the investment value by expressing the period of time required to recover the investment cost in a simple metric (i.e., year) [47-48, 56-57].

$$NPV_I = \sum_{t=1}^n \frac{BEG_t + BSI_t}{(1+r)^t} - \sum_{t=1}^n \frac{IC_t + OMC_t + TA_t}{(1+r)^t} \quad (1)$$

$$PI_I = \frac{\sum_{t=1}^n \frac{BEG_t + BSI_t}{(1+r)^t}}{\sum_{t=1}^n \frac{IC_t + OMC_t + TA_t}{(1+r)^t}} \quad (2)$$

where NPV_I stands for the net present value from the perspective of the investor, PI_I stands for the profitability index from the perspective of the investor, BEG_t stands for the benefit from the electricity generation in year t , BSI_t stands for the benefit from the solar incentives (i.e., FITC, SITC, CBI, and PBI) in year t , IC_t stands for the installation cost of the solar PV system

in year t , OMC_t stands for the operation and maintenance cost in year t , TA_t stands for the tax amount (i.e., property and sales tax) in year t , r stands for the real discount rate, and n stands for the analysis period.

Second, the LCC analysis result from the perspective of the government is presented in NPV to calculate the total incentive budget. As the incentive budget is an expense item, NPV from the perspective of the government considers only the cash outflows. That is, only the cost items are included in calculating the NPV from the perspective of the government, as expressed in Eq. (3). Therefore, PI and PP, which require benefit items for their calculation, are not taken into account for the LCC analysis result from the perspective of the government.

$$NPV_G = -\sum_{t=1}^n \frac{CSI_t}{(1+r)^t} \quad (3)$$

where NPV_G stands for the net present value from the perspective of the government, CSI_t stands for the cost of solar incentives (i.e., FITC, SITC, CBI, and PBI) in year t , r stands for the real discount rate, and n stands for the analysis period.

To calculate the LCC of different incentive and solar PV installation scenarios, several assumptions should be defined [2, 58]. First, the analysis period should be defined, and it is generally assumed to be 25 years based on the useful life and warranty period of the PV panel [59-60]. Second, the real discount rate should be calculated using Eq. (4), based on the nominal interest rate, inflation rate, electricity price growth rate, and CO₂ emission trading price growth rate. The information required for calculating the real discount rate was obtained from the following data: (i) the federal funds rate from 2005 to 2015 provided by the U.S. Federal Reserve Board; (ii) the inflation rate from 2005 to 2015 provided by USInflation.org; (iii) the annual average retail price of electricity by state from 2004 to 2015 provided by EIA; and (iv) the CO₂ emission trading price forecasts in the U.S. from 2020 to 2031 provided by the Synapse Energy Economics report [49, 61-63].

$$i = \frac{(1 + i_n)}{(1 + f)} - 1 \quad (4)$$

where i stands for the real discount rate; f stands for one of the followings: the inflation rate, electricity price growth rate, or CO₂ emission trading price growth rate; and i_n stands for the nominal interest rate.

Third, the significant cost of ownership, including the installation, maintenance, and replacement costs, should be defined. The installation cost can be assumed differently depending on the state and capacity, based on the average installed costs of the solar PV system provided by *The Open PV Project* [50]. The maintenance and replacement costs are generally assumed to be 1 and 9.5% of the installation cost of the solar PV system, respectively, based on the previous studies [22, 25]. Fourth, the degradation rate should be defined, and the performance of the solar PV system is generally assumed to be degraded by 20% during its 25-year useful life, based on the previous studies and the actual PV panel data [60, 64].

2.5. Step 5: Multi-objective optimization using a GA and Pareto optimal solutions

To solve the trade-off problem between the investor benefits and the government budget through multi-objective optimization, this study used GA and Pareto optimal solutions.

First, GA was used to find the optimal solution to the optimization problem. GA finds the candidate solution to the optimization problem by continuously changing a population of *chromosomes* to a better one based on the principles of natural selection and genetics. To find the potential solutions to the optimization problem and to evaluate them according to the optimization objective, GA requires a fitness function, which returns a value that quantifies how good a particular solution is at solving a problem [65-67].

Second, Pareto optimal solutions were used to find the optimal solution to the multi-objective optimization problem. The Pareto optimal solution set, a method most commonly

adopted in multi-objective optimization, is a set of solutions where the performance cannot be improved in one objective without degrading it in the other objective [68]. In this study, a total of five optimization objectives were used to solve various trade-off problems from the perspectives of the investor and the government: (i) from the investor's perspective: initial investment cost, investor benefits_{NPV}, investor benefits_{PI}, and PP; and (ii) from the government's perspective: total incentive budget (refer to Table III).

A representative set of Pareto optimal solutions that satisfy different objectives can be found using the proposed fitness function expressed in Eq. (5), based on the weighted Euclidean distance [69-71]. Using Eq. (5), the values of objective functions A to E could be maximized or minimized depending on the characteristics of the optimization objectives. As shown in Eq. (5), objective functions A, D, and E target to minimize their values while the objective functions B and C target to maximize their values. That is, the closer the values of objective functions A, D, and E are to the minimum, the more optimal they are, whereas the closer the values of objective functions B and C are to the maximum, the more optimal they are. Meanwhile, the relative weights of objective functions are selected considering the trade-off relationships between the investor benefit and the government budget. Among the five optimization objectives, four (i.e., A, B, C, and D) of them are related to the profitability from the investor's perspective whereas only one (i.e., E) of them is related to the expenditure from the government's perspective. Accordingly, the sum of the relative weights of objective functions A to D is defined to be equal to that of objective function E (refer to Eq. (6)). The optimization process continues until the value of the fitness function, defined as the iMOO score, reaches its minimum, where the optimal solar incentives are found.

$$\text{Fitness Function}(i) = \sqrt{W_A \times (S_A - 0)^2 + W_B \times (1 - S_B)^2 + W_C \times (1 - S_C)^2 + W_D \times (S_D - 0)^2 + W_E \times (S_E - 0)^2} \quad (5)$$

$$W_A + W_B + W_C + W_D = W_E \quad (6)$$

where W_A , W_B , W_C , W_D , and W_E stand for the relative weights of objective functions A (i.e., initial investment cost), B (i.e., investor benefits_{NPV}), C (i.e., investor benefits_{PI}), D (i.e., PP), and E (i.e., total incentive budget), respectively, defined by the final decision-maker; S_A , S_B , S_C , S_D , and S_E stand for the standardized values of objective functions A, B, C, D, and E, respectively; and the value of the fitness function stands for the iMOO score.

2.6. Step 6: Microsoft-Excel-based iMOO model development

By integrating and incorporating the process from step 1 to 5, this study developed a Microsoft-Excel-based iMOO model to automatically solve the trade-off problem between the investor benefits and the government budget, and to determine the optimal solar incentive design in the U.S. The graphical user interface of the Microsoft-Excel-based iMOO model consists of four sections as follows: (i) basic information; (ii) assumptions; (iii) optimization; and (iv) results. Among these four sections, Fig. 2 shows the graphical user interface of section 3, the main section displaying the multi-objective optimization process. The graphical user interface of other sections (i.e., sections 1, 2, and 4) are presented as Supporting Information, SI Figs. S1-S3 with a short description.

Section 3, “Optimization” section, consists of three phases: (i) optimization objectives; (ii) solar incentives; and (iii) constraints. First, to determine the optimal solar incentive design through the optimization process, optimization objectives should be selected by the system user. Using the standardized values and relative weights of the selected optimization objective, the iMOO score is calculated (refer to Part (A) in Fig. 2). Second, the system user can select types of solar incentives to be considered in determining the optimal solar incentive design. This can be done by selecting the payment option from the drop box: adjustable, fixed, and not offered. To determine the optimal amount for a certain type of solar incentive through the optimization process, the payment option can be set to “adjustable”. In this case, the range and cap of the

relevant solar incentive should be entered by the system user. To assign a fixed amount or 0 for a certain type of solar incentive by the system user, the payment option can be set to “fixed” or “not offered”. In this case, the relevant solar incentive would be fixed at one value and not be taken into account during the optimization process for determining the optimal solar incentive design (refer to Part (B) in Fig. 2). Third, the system user can limit the cash incentive budget by entering the maximum cash incentive budget that can be supported by the government or electric utilities in the blue-colored box (refer to Part (C) in Fig. 2).

PViOpt Photovoltaic Incentive Optimization
The Multi-Objective Optimization System for Determining the Optimal Solar Incentive Design of the PV system

BASIC INFORMATION

ASSUMPTIONS

OPTIMIZATION

RESULTS

OPTIMIZATION

Optimization Objectives

	Value	Minimum	Maximum	Standardized value	Weight	Optimization goal
<input type="checkbox"/> Initial investment cost	\$ 13,918.68	-	32,664.46	0.43	1.00	minimization
<input checked="" type="checkbox"/> Investor benefits _{NPV}	\$ 12,462.35	- 8,596	23,034.75	0.67	1.00	maximization
<input type="checkbox"/> Investor benefits _{P1}	1.327	0.826	1.605	0.64	1.00	maximization
<input checked="" type="checkbox"/> Payback period	11 yrs	0	25	0.44	1.00	minimization
<input checked="" type="checkbox"/> Total incentive budget	\$ 16,083.12	9,799	30,001.80	0.31	2.00	minimization
IMOO score	0.35					minimization

Solar Incentives

	Rate	Payment Option	Fixed Amount	Range	Cap
Federal Investment Tax Credit (FITC)	30 %	Fixed	30 %	0 - 30 %	\$ -
State Investment Tax Credit (SITC)	29 %	Adjustable	25 %	0 - 100 %	\$ -
Property Tax Exemption (PTE)	100 %	Adjustable	90 %	0 - 100 %	\$ -
Sales Tax Exemption (STE)	100 %	Adjustable	90 %	0 - 100 %	\$ -
Capacity-based incentives (CBI)	322 \$/kW	Adjustable	120 \$/kW	- - 3,000 \$/kW	\$ -
Performance-based incentives (PBI)	- \$/kWh	Adjustable	0.05 \$/kWh	- - 0.30 \$/kWh	15 yr(s) <input type="checkbox"/> SREC

Constraints

	Value	Maximum
Cash incentive budget	\$ 1,996.40	\$ 6,200

Figure 2. Graphical user interface of the excel-based iMOO model (Section 3)

3. MODEL APPLICATION

In this study, to verify the effectiveness of the developed iMOO model, the iMOO model was applied to determine the optimal solar incentive design in the U.S. Towards this end, several information regarding the multi-objective optimization process for the model application were determined: (i) the target values for the regions (states and cities), facility, and installed capacity of the solar PV system; (ii) the LCC and system assumptions; and (iii) the optimization information (refer to Table IV).

First, this study selected the target values for the regions (states and cities), facility, and installed capacity of the solar PV system for the model application. The top three states (i.e., Massachusetts (MA), New Jersey (NJ), and New York (NY)) with excellent solar policies and incentives, and the bottom three states (i.e., Arkansas (AR), Oklahoma (OK), and Wyoming (WY)) with poor solar policies and incentives were selected as the target states, according to the state solar power rankings provided by *Solar Power Rocks*. *Solar Power Rocks*, a website with comprehensive guides to solar policy and incentives, provides the state solar power rankings considering current solar policies (i.e., Renewable Portfolio Standards, Solar Carve-Out, electricity cost, net metering, and interconnection) and incentives (i.e., FITC, SITC, PTE, STE, CBI, and PBI) offered in all 50 states and the District of Columbia [72]. As the solar radiation can be different within the same state, the metropolitan city that has the largest population in each state (i.e., Boston in Massachusetts, Newark in New Jersey, New York City in New York, Little Rock in Arkansas, Oklahoma City in Oklahoma, and Cheyenne in Wyoming) was selected as the target city for that target state [47]. The residential and 6.2 kW solar PV system were selected as the target facility and the target installed capacity of the solar PV system, respectively, according to the average installed capacity of the residential solar PV system provided by *Tracking the Sun VIII*, the latest publication on the historical data on the installation cost of the solar PV system in the U.S., by Lawrence Berkeley National Laboratory

[9]. A uniform 6.2 kW residential solar PV system in six different states was selected as the target for the model application to show how the developed iMOO model determines the optimal solar incentive designs in different regions and to compare them under the same condition (i.e., same installed capacity), as a 6.2 kW system represents the widely installed residential solar PV system in the U.S.; however, it is always possible to determine the optimal solar incentive design for solar PV systems with different conditions (i.e., different installed capacity and facility type) by using the developed iMOO model.

Second, the LCC and system assumptions for the model application were defined, as follows: (i) analysis period; (ii) real discount rate; and (iii) significant cost of ownership. The detailed LCC and system assumptions are specifically described in section 2.4 (“Step 4: LCC analysis”).

Third, the following optimization information were established for the model application: (i) optimization objectives; (ii) adjustable parameters; and (iii) constraint parameter.

- *Optimization objectives:* A total of five optimization objectives were selected for the model application, as follows: (i) initial investment cost; (ii) investor benefits_{NPV}; (iii) investor benefits_{PI}; (iv) PP; and (v) total incentive budget. As four (i.e., initial investment cost, investor benefits_{NPV}, investor benefits_{PI}, and PP) of them are related to the profitability from the investor’s perspective and one (i.e., total incentive budget) of them is related to the expenditure from the government’s perspective, the relative weights for total incentive budget was set at four, which is the sum of the relative weights for initial investment cost, investor benefits_{NPV}, investor benefits_{PI}, and PP. Furthermore, the relative weights for aforementioned four optimization objectives which indicate the profitability from the investor’s perspective were equally set at one, respectively, in order to consider each of them fairly without any preference.
- *Adjustable parameters:* A total of five types of solar incentives were selected as

adjustable parameters for the model application, as follows: (i) SITC; (ii) PTE; (iii) STE; (iv) CBI; and (v) PBI. As the federal government currently offers a fixed FITC rate (i.e., 30%) for all states, FITC was fixed at 30% during the optimization process. Other than FITC, each type of solar incentive (i.e., adjustable parameters) is assumed to be offered within a certain range during the optimization process to determine a practical and reasonable incentive rate. The range of each adjustable parameter was established based on the actual incentive rates currently being paid using the information on the state solar incentives provided by *Database of State Incentives for Renewables & Efficiency (DSIRE)* [48, 51].

- *Constraint parameter:* The cash incentive budget was selected as a constraint parameter for the model application. According to the information on the cash incentives provided by *Tracking the Sun VIII*, the direct cash incentives largely declined to below US\$1,000/kW in many key solar markets [9]. As such, the cash incentive budget was limited to US\$6,200 ($= 6.2\text{kW} \times \text{US\$1,000/kW}$) to determine a practical and reasonable solar incentive design during the optimization process.

4. RESULTS AND DISCUSSION

This study conducted model application using the developed iMOO model to determine the optimal solar incentive design for six target regions in the U.S. As a result, an optimal solar incentive design for each target region was retrieved among the 781,677,647,751 ($= 51$ (number of cases for SITC) \times 101 (number of cases for PTE) \times 101 (number of cases for STE) \times 1,501 (number of cases for CBI) \times 1,001 (number of cases for PBI)) possible incentive scenarios. In addition, to compare the economic performance of the optimal solar incentives with that of the current solar incentives, LCC analysis of the solar PV system was also conducted considering the current solar incentives offered by each target region. The solar

renewable energy certificate (SREC), which is issued when 1 MWh of electricity is generated from solar energy, was not considered in the calculation of the LCC of the solar PV system in this study, because the SREC market could be operated similarly as the stock market, unlike the other solar incentives, which are directly offered by the government or electric utilities [6]. Using the developed iMOO model, however, it is also possible to determine the optimal SREC price acceptable in a certain target region. Table V shows the optimization results for determining the optimal solar incentive design with the developed iMOO model along with the LCC analysis results of the current solar incentives in the six target regions. As shown in Table V, the iMOO score for the optimal incentive scenario in each target region was minimized through the optimization process, varying from 0.3558 to 0.4605 depending on the target region. When the determined optimal incentives for each target region are offered, the economic performance from the investor's (i.e., initial investment cost, investor benefits_NPV, investor benefits_PI, and PP) and government's (i.e., total and cash incentive budget) perspectives per 6.2kW residential solar PV system installed would appear to be as shown in Table V. Detailed analysis results would be discussed below.

4.1. Optimization results for determining the optimal solar incentive design

Fig. 3 shows the optimal solar incentive design determined using the developed iMOO model, and the relevant optimization results in the six target regions. Overall, different optimal solar incentive designs were retrieved for all the six target regions (refer to Table V and Fig. 3). The detailed analysis can be found below.

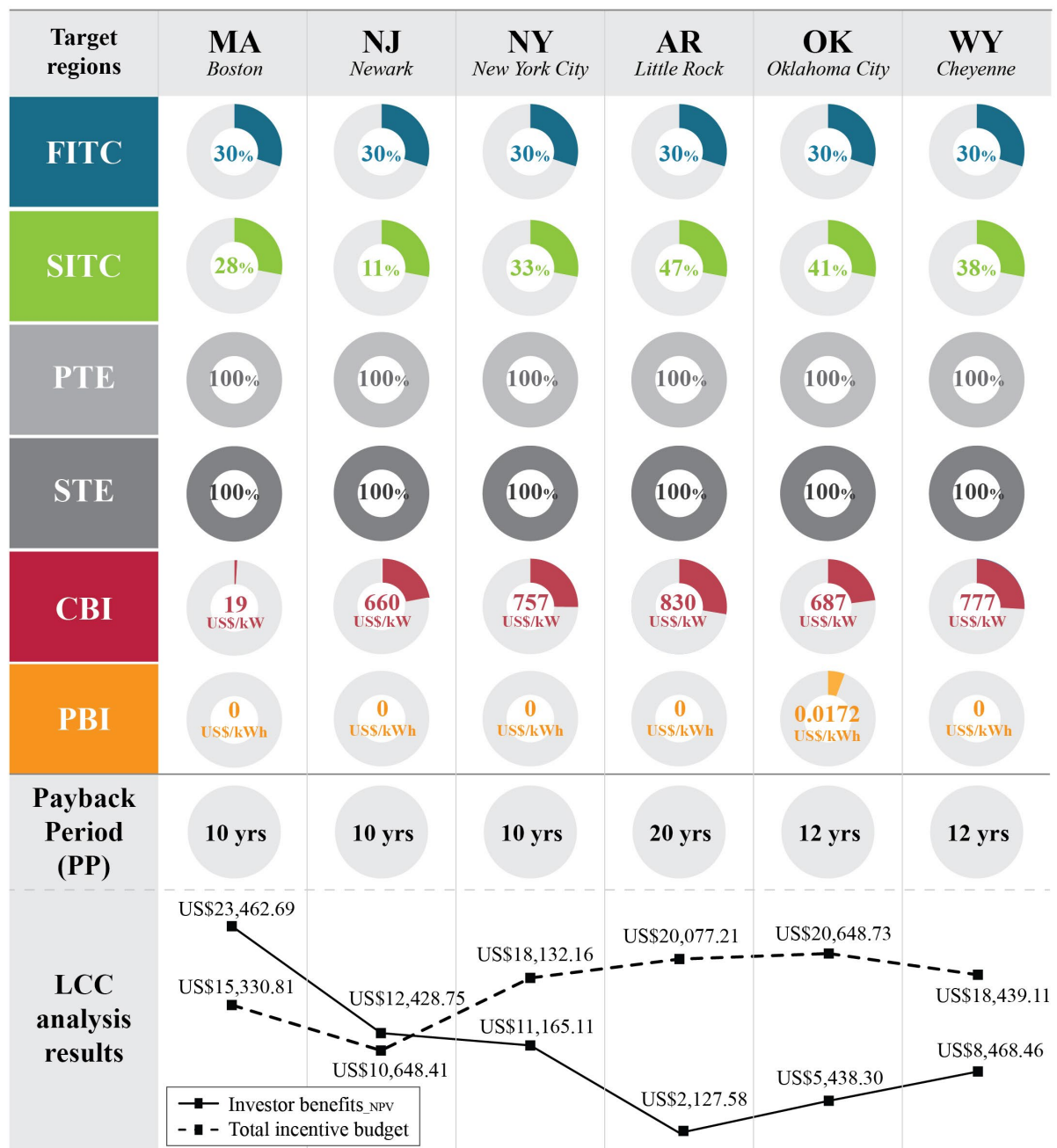


Figure 3. The optimal solar incentive design and LCC analysis results in the six target regions

First, the target regions in the top three states with excellent solar policies and incentives (i.e., Boston, MA; Newark, NJ; and New York City, NY) required less incentive budget (i.e., a total incentive budget of US\$10,648.41-18,132.16) than the target regions in the bottom three states with poor solar policies and incentives (i.e., Little Rock, AR; Oklahoma City, OK; and

Cheyenne, WY), which required the total incentive budget of US\$18,439.11-20,648.73, for maximizing the investor benefits while minimizing the government budget. Accordingly, from the aspect of the optimal solar incentive design, in all the target regions in the top three states (i.e., Boston, Newark, and New York City), the optimal SITC and CBI were determined to have a rate under 33% (i.e., 28, 11, and 33%, respectively) and US\$757/kW (i.e., US\$19/kW, US\$660/kW, and US\$757/kW, respectively), whereas it was determined to have a rate over 38% (i.e., 47, 41, and 38%, respectively) and US\$687/kW (i.e., US\$830/kW, US\$687/kW, and US\$777/kW, respectively) in all the target regions in the bottom three states (i.e., Little Rock, Oklahoma City, and Cheyenne). It can be said that the target regions in the top three states required a relatively low incentive budget compared to the target regions in the bottom three states to maximize the investor benefits, mainly due to the high electricity prices (refer to Table VI). Although the solar radiation is relatively low in the target regions in the top three states, resulting in low electricity generation from solar energy, a high electricity price allows maximizing the electricity generation benefit from the perspective of the investor. On the other hand, the electricity price is too low in the target regions in the bottom three states to obtain a high electricity generation benefit even with relatively high solar radiation.

Second, although a higher incentive budget was required for the optimal solar incentive design in the target regions in the bottom three states, the economic performance of the solar PV system was higher in the target regions in the top three states when the optimal solar incentive was offered. Even without high solar incentives, the target regions in the top three states showed a high economic performance of the solar PV system from the investor's perspective (i.e., US\$11,165.11-23,462.69 investor benefits_{NPV}; 1.29-1.60 investor benefits_{PI}; and 10 years PP), whereas the target regions in the bottom three states showed a relatively low economic performance of the solar PV system in terms of the investor's perspective (i.e., US\$2,127.58-8,468.46 investor benefits_{NPV}, 1.06-1.23 investor benefits_{PI}, and 12-20 years PP)

even with high solar incentives. This indicates that it is easy to guarantee the economic feasibility with a small amount of incentive budget in the target regions in the top three states where a high electricity generation benefit can be obtained, whereas it is hard to expect high economic feasibility even with a large amount of incentive budget in the target regions in the bottom three states due to low electricity generation benefit (refer to Table VI).

Third, among the six target regions, the optimal solar incentive design in Newark with a 30% FITC, an 11% SITC, 100% PTE and STE, and US\$660/kW CBI required the lowest incentive budget of US\$10,648.41 due to its low installation cost and high electricity price (refer to Table VI). Boston, which showed the highest electricity generation benefit due to its remarkably high electricity price, required higher incentive budget (i.e., US\$15,330.81) for its optimal solar incentive design (i.e., 30% FITC, 28% SITC, 100% PTE and STE, and US\$19/kW CBI) due to its high installation cost compared to Newark; however, the investor benefits_{NPV} in Boston (i.e., US\$23,462.69) was almost twice as much as that in Newark (i.e., US\$12,428.75) when each of their optimal solar incentives were offered. This indicates that a low installation cost minimizes the total incentive budget required for the optimal solar incentive design while a high electricity generation benefit maximizes the investor benefits for determining the optimal solar incentive design using the developed iMOO model.

Fourth, Oklahoma City required the highest incentive budget of US\$20,648.73 among the six target regions for its optimal solar incentive design (i.e., 30% FITC, a 41% SITC, 100% PTE and STE, US\$687/kW CBI, and US\$0.0172/kWh PBI) due to its low electricity price (refer to Table VI). Little Rock, showing the lowest electricity generation benefit due to its low solar radiation and low electricity price, required a slightly lower incentive budget of US\$20,077.21 for its optimal solar incentive design (i.e., 30% FITC, 47% SITC, 100% PTE and STE, and US\$830/kW CBI) compared to Oklahoma City, but the economic performance of the solar PV system in Little Rock (i.e., US\$2,127.58 investor benefits_{NPV}, 1.06 investor

benefits_{PI}, and 20 years PP) was far worse than that in Oklahoma City (i.e., US\$5,438.30 investor benefits_{NPV}, 1.15 investor benefits_{PI}, and 12 years PP) when their optimal solar incentives were offered, respectively. This indicates that the developed iMOO model does not continuously increase the incentive budget to maximize the investor benefits during the optimization process for determining the optimal solar incentive design. Rather, it finds the balance point to solve the trade-off problem between the investor benefits and the government budget.

In summary, it was shown that depending on the various key factors affecting the technical and economic performance of the solar PV system (e.g., solar radiation, electricity price, installation cost) of each region, the optimal solar incentive design can be determined differently using the developed iMOO model. That is, it is possible to determine and establish the optimal solar incentive design that is reasonable and acceptable in a particular region considering the decision-maker's preferences with the developed iMOO model.

4.2. Trade-off analysis between the optimization objectives

In order to validate the reliability of the optimal solar incentive design determined by using the developed iMOO model, this study conducted the trade-off analysis between the optimization objectives. Prior to the detailed trade-off analysis, the correlation analysis among the five optimization objectives was conducted using the log of all trials during the optimization process of the model application in six target regions (refer to Table VII and SI Tables S1-S5). As mentioned in Chapter 2.5., “Step 5: Multi-objective optimization using a GA and Pareto optimal solutions”, three optimization objectives (i.e., initial investment cost, PP, and total incentive budget) target to minimize their values while two optimization objectives (i.e., investor benefits_{NPV} and investor benefits_{PI}) target to maximize their values. Accordingly, when there is any trade-off relationship between the optimization objectives, one would get

closer to its optimal value, no matter what it targets (i.e., maximizing or minimizing), while the other would get further from its optimal value. For example, if there is a trade-off relationship between the investor benefits_{NPV} and the total incentive budget, then the investor benefits_{NPV} would get closer to the maximum (i.e., the optimal value), while the total incentive budget would get further from the minimum (i.e., the optimal value).

As a result of the correlation analysis among the five optimization objectives, it was shown that all four optimization objectives which are related to the profitability from the investor's perspective (i.e., initial investment cost, investor benefits_{NPV}, investor benefits_{PI}, and PP) have the trade-off relationship with the optimization objective which is related to the expenditure from the government's perspective (i.e., total incentive budget). As the results of the correlation analysis showed similar patterns for all six target regions, the detailed results mostly on Boston, MA were discussed below to avoid unnecessary repetition. As shown in Table VII and SI Tables S1-S5, the total incentive budget has positive correlations with the investor benefits_{NPV} and investor benefits_{PI}, and negative correlations with the initial investment cost and PP, implying the total incentive budget has the trade-off relationship with all other optimization objectives. As the total incentive budget targets to minimize its value while the investor benefits_{NPV} and investor benefits_{PI} target to maximize their values, positive correlations between the former (i.e., total incentive budget) and the latter (i.e., investor benefits_{NPV} and investor benefits_{PI}) indicate that they have trade-off relationships. Similarly, as the total incentive budget, initial investment cost, and PP target to minimize their values, negative correlations between them indicate that they have trade-off relationships. Accordingly, the trade-off analysis between the total incentive budget and the other four optimization objectives (i.e., initial investment cost, investor benefits_{NPV}, investor benefits_{PI}, and PP) was conducted to validate the reliability of the optimal solutions and prove that the Pareto optimal solutions have been found.

Fig. 4 shows the result of the trade-off analysis between the total incentive budget and the other four optimization objectives (i.e., initial investment cost, investor benefits_{NPV}, investor benefits_{PI}, and PP) for the model application in Boston, MA. Along with Fig. 4, the log of progress steps during the optimization process of the model application in Boston, MA has been presented in Table VIII to provide detailed information on representative trials during the optimization process. Representatively, in Fig. 4(B), as the investor benefits_{NPV} targets to maximize its value while the total incentive budget targets to minimize its value during the optimization process, the Pareto optimal solutions are expected to be found near coordinate (1,0). By plotting the log of all trials (i.e., grid in red (i.e., high iMOO score) to blue (i.e., low iMOO score (optimized)) color scale) and progress steps (i.e., white circles with black outlines) in Fig. 4, it can be seen that the trials move towards the coordinate (1,0) as the optimization proceeds (refer to the direction of the arrows in Fig. 4), which indicates that the proposed iMOO model is capable of finding the Pareto optimal solutions. As a result, the optimal solution (i.e., the red circle with black outline) was found to have the iMOO score of 0.3796, and the total incentive budget and investor benefits_{NPV} were determined at US\$15,331 and US\$23,463, respectively. Similar patterns had been found in the trade-off analysis results for other five target regions and they are presented in SI Figs. S4-S8 to avoid unnecessary repetition.

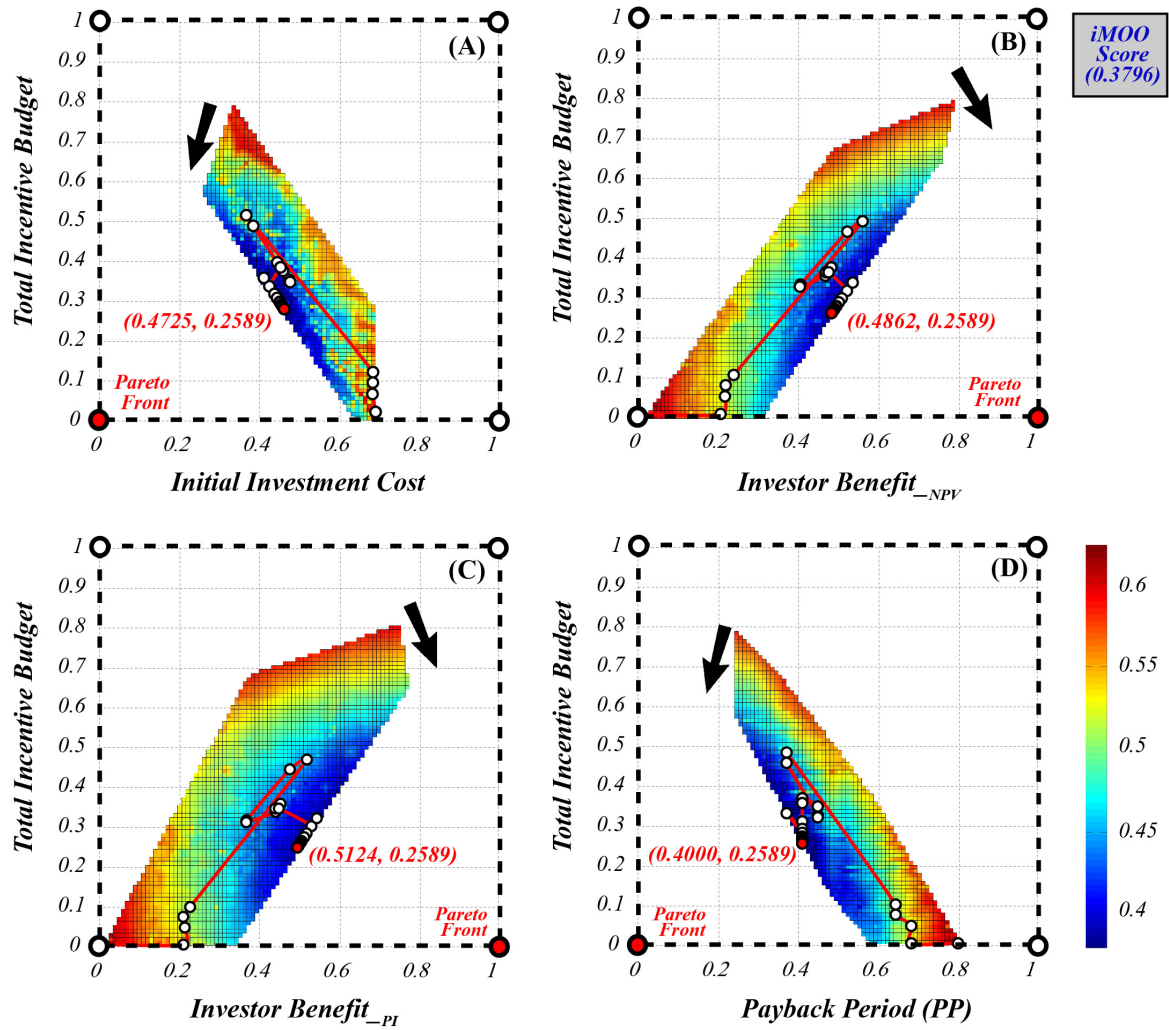


Figure 4. Surface plot with the interpolated iMOO score of the optimization objectives in Boston, MA

4.3. Comparative analysis of the current and optimal solar incentive designs

Fig. 5 compares the LCC analysis results of the current and optimal solar incentive designs in the six target regions. Overall, the economic performance of the solar PV system from the perspective of the investor was improved by applying the optimal solar incentive design determined using the developed iMOO model in all the target regions compared to the current solar incentive design. Accordingly, the total incentive budget from the perspective of the government was increased by applying the optimal solar incentive design in all the target regions (refer to Table V and Fig. 5). The detailed analysis can be found below.

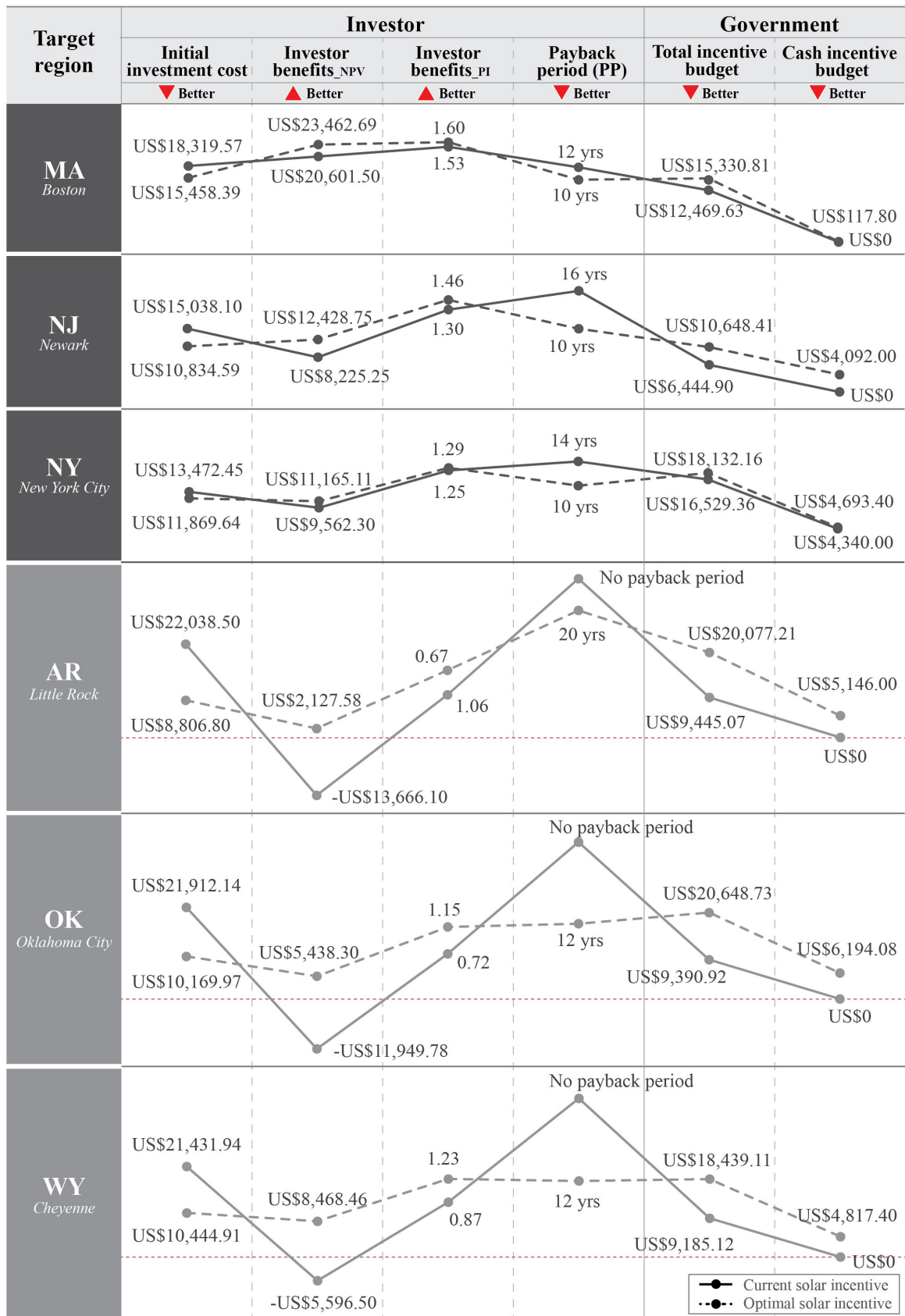


Figure 5. The LCC analysis results of the current and optimal solar incentive design in the six target regions

First, it was shown that the target regions in the top three states (Boston, Newark, and New York City) do not necessarily need improvement of the solar incentive using the developed iMOO model because their current solar incentive design already has sufficient economic feasibility (i.e., US\$8,225.25-20,601.50 investor benefits_{NPV}, 1.25-1.53 investor benefits_{PI}, and 12-16 years PP). It is still possible, however, to improve the solar incentive design if the decision-maker wants to strongly promote solar PV system installation to investors using the developed iMOO model because the economic performance of the solar PV system from the perspective of the investor was improved by applying the optimal solar incentive design compared to the current solar incentive design in these three target regions. By offering the optimal solar incentives determined using the developed iMOO model in Boston, Newark, and New York City, investor benefits_{NPV} could be improved from US\$20,601.50 to US\$23,462.69, from US\$8,225.25 to US\$12,428.75, and from US\$9,562.30 to US\$11,165.11, respectively, and the PP could be shortened from 12, 16, and 14 years, respectively, to 10 years. For these improvements, however, the government or electric utilities should be willing to spend an extra incentive budget of US\$2,861.18 in Boston, US\$4,203.51 in Newark, and US\$1,602.80 in New York City for a 6.2 kW solar PV system.

Second, it was shown that the target regions in the bottom three states (i.e., Little Rock, Oklahoma City, and Cheyenne) need improvement of the solar incentive using the developed iMOO model because these target regions, where there is no financial support through solar policies and incentives, could not guarantee economic feasibility (i.e., US\$-13,666.10 to US\$-5,596.50 investor benefits_{NPV}, 0.67-0.87 investor benefits_{PI}, and no PP). By offering the optimal solar incentives determined using the developed iMOO model in these three target regions, the investor benefits_{NPV} could be improved from US\$-13,666.10 to US\$-2,127.58, from US\$-11,949.78 to US\$5,438.30, and from US\$-5,596.50 to US\$8,468.46, respectively, and a PP of 20, 12, and 12 years, respectively, could be achieved. For these improvements,

however, the government or electric utilities should be willing to spend an extra incentive budget of US\$10,632.14 in Little Rock, US\$11,257.81 in Oklahoma City, and US\$9,253.99 in Cheyenne for a 6.2 kW solar PV system.

5. CONCLUSIONS

In this study, an iMOO model was developed for determining the optimal solar incentive design from the perspectives of the investor and the government. Towards this end, various methodologies were used to develop the Microsoft-Excel-based iMOO model, such as LCC analysis, GA, and the Pareto optimal solutions. The developed Microsoft-Excel-based iMOO model was applied to six target regions (Boston, MA; Newark, NJ; New York City, NY; Little Rock, AR; Oklahoma City, OK; and Cheyenne, WY) to determine the optimal solar incentive design in each of them. Furthermore, the LCC analysis results of the optimal solar incentive design determined by the developed iMOO model were compared to those of the current solar incentive design in the six target regions to show how the solar incentive design can be improved.

As a result of the model application, the optimal solar incentive designs in the six target regions were determined. The optimal solar incentive design determined by the developed iMOO model varied across the target regions, as follows: (i) FITC was fixed at 30% for all the target regions; (ii) SITC varied from 11 to 47% depending on the target region; (iii) both the PTE and the STE were determined to be 100% for all the target regions; (iv) the CBI varied from US\$19/kW to US\$830/kW depending on the target region; and (v) the PBI varied from US\$0/kWh to US\$0.0172/kWh depending on the target region. Accordingly, the total incentive budget required for the optimal solar incentive design changed from US\$10,648.41 to US\$20,648.73 depending on the target region. Among the six target regions, Newark required the lowest incentive budget of US\$10,648.41 for the optimal solar incentive design due to its

low installation cost and high electricity price, whereas Boston showed the highest investor benefits_{NPV} of US\$23,462.69 with its optimal solar incentive design due to its high electricity generation benefit. Meanwhile, among the six target regions, Oklahoma City required the highest incentive budget of US\$20,648.73 for the optimal solar incentive design due to its low electricity price, whereas Little Rock showed the worst economic performance of the solar PV system (i.e., US\$2,127.58 investor benefits_{NPV}, 1.06 investor benefits_{PI}, and 20 years PP) with its optimal solar incentive design due to its low electricity generation benefit. The LCC analysis results of the current and optimal solar incentive designs in the six target regions were also compared. It was shown that solar incentive design improvement was not necessary in Boston, Newark, and New York City, the target regions in the top three states, since the solar PV system with the current solar incentive design had sufficient economic feasibility in these regions. Meanwhile, solar incentive design improvement was necessary in Little Rock, Oklahoma City, and Cheyenne, the target regions in the bottom three states, whose solar PV system with the current solar incentive design had no economic feasibility.

The developed iMOO model is superior to the models and methods from the previous studies in terms of effectiveness and usefulness in that it (i) uses reasonable and realistic data, which makes it more accurate and reliable; (ii) considers various optimization objectives from the perspectives of the investor and the government through multi-objective optimization; (iii) solves the various trade-off problems between the investor benefits and the government budget; and (iv) is oriented towards the system users by allowing them to select optimization options according to their preferences. Although it is not directly shown in the model application, it is possible for the state governments and electric utilities to establish various strategies for solar policies and incentives by using the proposed iMOO model as it provides some guidelines for determining a specific incentive rate for each type of solar incentives depending on different conditions (i.e., region, installed capacity, and facility type).

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Table I

Literature reviews on the solar incentives

Classification		References
Evaluation	Financial analysis of solar policies and incentives	Janko et al. [21], Swift [22], Fathoni et al. [23], Flores et al. [24], Burns and Kang [25], Jiang and Zhu [26], Mulder et al. [27], Cucchiella and D'Adamo [28], Lee et al. [47].
	Impact analysis of solar policies and incentives	Coffman et al. [29], Comello and Reichelstein [30], Ahmad et al. [31], Jung and Tyner [32], Sawhney et al. [33], Reichelstein and Yorston [34], Rodrigues et al. [35], Sahu [36], Mayr et al. [37], Dusonchet and Telaretti [38], Campoccia et al. [39], Ismail et al. [40], Lee et al. [48].
Optimization	Perspective of the government	Kim and Lee [41], Das et al. [45].
	Perspectives of the government and investor	Das and Cañizares [42], Chen and Song [43], Chen & Hong [44], Jeon et al. [46].

Table II

Classification of solar incentives in the U.S.

Classification		Adjustable variables	Sample values	Unit
Tax Incentives	Investment Tax Credit	Federal Investment Tax Credit (FITC)	30	%
		State Investment Tax Credit (SITC)	25	%
	Tax Exemption	Property Tax Exemption (PTE)	100	%
		Sales Tax Exemption (STE)	0	%
Cash Incentives		Capacity-Based Incentives (CBI)	100	US\$/kW
		Performance-Based Incentives (PBI)	0.10	US\$/kWh

Table III

Five optimization objectives from the perspectives of the investor and government

Perspective	Optimization objectives	Optimization goal
Investor	Initial investment cost	Minimization
	Investor benefits _{NPV}	Maximization
	Investor benefits _{PI}	Maximization
	Payback period (PP)	Minimization
Government	Total incentive budget	Minimization

Table IV
Information on optimization process for model application

Classification	Variables	Detailed description
Optimization objectives	Initial investment cost	Goal: minimization, Weight: 1
	Investor benefits _{NPV}	Goal: maximization, Weight: 1
	Investor benefits _{PI}	Goal: maximization, Weight: 1
	Payback period (PP)	Goal: minimization, Weight: 1
	Total incentive budget	Goal: minimization, Weight: 4
Defined parameters	Region	Boston, MA
		Newark, NJ
		New York City, NY
		Little Rock, AR
		Oklahoma City, OK
		Cheyenne, WY
	Facility type	Residential
	Orientation	South
	Tilt of the solar PV system	optimal tilt by region
	Installed capacity of the solar PV system	6.2 kW
Adjustable parameters	Federal Investment Tax Credit (FITC)	30%
	State Investment Tax Credit (SITC)	Range: 0% - 50%
	Property Tax Exemption (PTE)	Range: 0% - 100%
	Sales Tax Exemption (STE)	Range: 0% - 100%
	Capacity-based incentives (CBI)	Range: US\$0/kW - US\$1,500/kW
	Performance-based incentives (PBI)	Range: US\$0/kWh - US\$0.1/kWh for 15 years
Constraint parameters	Cash incentive budget (NPV)	Limit: US\$6,200

Table V

Optimization results for determining the optimal solar incentive design in six target regions with the developed iMOO model

Target region	Incentive Scenario	Solar incentive design						Investor			Government			iMOO score
		FITC	SITC	PTE	STE	CBI (US\$/kW)	PBI (US\$/kWh)	Initial investment cost (US\$)	Investor benefits _{NPV} (US\$)	Investor benefits _{PI}	Payback period (PP) (years)	Total incentive budget (US\$)	Cash incentive budget (US\$)	
Boston, MA	Current	30%	15%	100%	100%	-	-	18,319.57	20,601.50	1.53	12	12,469.63	-	-
	Optimal	30%	28%	100%	100%	19	-	15,458.39	23,462.69	1.60	10	15,330.81	117.80	0.3796
Newark, NJ	Current	30%	-	100%	100%	-	-	15,038.10	8,225.25	1.30	16	6,444.90	-	-
	Optimal	30%	11%	100%	100%	660	-	10,834.59	12,428.75	1.46	10	10,648.41	4,092.00	0.3558
New York City, NY	Current	30%	25%	100%	100%	700	-	13,472.45	9,562.30	1.25	14	16,529.36	4,340.00	-
	Optimal	30%	33%	100%	100%	757	-	11,869.64	11,165.11	1.29	10	18,132.16	4,693.40	0.3897
Little Rock, AR	Current	30%	-	-	-	-	-	22,038.50	-13,666.10	0.67	n/a	9,445.07	-	-
	Optimal	30%	47%	100%	100%	830	-	8,806.80	2,127.58	1.06	20	20,077.21	5,146.00	0.4605
Oklahoma City, OK	Current	30%	-	-	-	-	-	21,912.14	-11,949.78	0.72	n/a	9,390.92	-	-
	Optimal	30%	41%	100%	100%	687	0.0172	10,169.97	5,438.30	1.15	12	20,648.73	6,194.08	0.4274
Cheyenne, WY	Current	30%	-	-	-	-	-	21,431.94	-5,596.50	0.87	n/a	9,185.12	-	-
	Optimal	30%	38%	100%	100%	777	-	10,444.91	8,468.46	1.23	12	18,439.11	4,817.40	0.4191

Note: n/a refers that the target city cannot achieve PP within 25 years.

Table VI

Key factors affecting the technical and economic performance of the solar PV system in six target regions

Target region	Annual electricity generation (kWh)	Average Electricity price (US\$/kWh)	Electricity generation benefit (US\$)	Installation cost (US\$)
Boston, MA	8,868	0.1980	47,190.21	30,789
Newark, NJ	8,300	0.1589	29,033.09	21,483
New York City, NY	8,543	0.1854	31,092.41	30,002
Little Rock, AR	8,909	0.0988	18,691.84	28,884
Oklahoma City, OK	10,223	0.1010	21,431.05	28,884
Cheyenne, WY	10,313	0.1105	26,670.83	28,884

Table VII

Correlation analysis among the optimization objectives for the model application in Boston, MA

Optimization objectives		Initial investment cost	Investor benefits _{NPV}	Investor benefits _{PI}	Payback period (PP)	Total incentive budget
Initial investment cost	Pearson correlation	1	-.884**	-.836**	.909**	-.880**
	Sig. (2-tailed)	-	0	0	0	0
	N	9312	9312	9312	9312	9312
Investor benefits _{NPV}	Pearson correlation	-.884**	1	.988**	-.977**	.757**
	Sig. (2-tailed)	0	-	0	0	0
	N	9312	9312	9312	9312	9312
Investor benefits _{PI}	Pearson correlation	-.836**	.988**	1	-.951**	.658**
	Sig. (2-tailed)	0	0	-	0	0
	N	9312	9312	9312	9312	9312
Payback period (PP)	Pearson correlation	.909**	-.977**	-.951**	1	-.795**
	Sig. (2-tailed)	0	0	0	-	0
	N	9312	9312	9312	9312	9312
Total incentive budget	Pearson correlation	-.880**	.757**	.658**	-.795**	1
	Sig. (2-tailed)	0	0	0	0	-
	N	9312	9312	9312	9312	9312

Note: ** Correlation coefficient is significant at 0.01 level (both sides).

Table VIII

The log of progress steps during the optimization process of the model application in Boston, MA

Step	Adjustable parameters					Standardized values of optimization objectives (0-1)					iMOO score
	SITC (%)	PTE (%)	STE (%)	CBI (US\$/kW)	PBI (US\$/kWh)	Initial investment cost	Investor benefits NPV	Investor benefits PI	Payback period (PP)	Total incentive budget	
1	0	90	0	0	0	0.7000	0.2045	0.2112	0.6800	0.0000	0.5253
2	0	81	0	60	0	0.6920	0.2156	0.2146	0.6800	0.0455	0.5222
3	0	73	0	54	0	0.6928	0.2173	0.2105	0.6400	0.0741	0.5181
4	0	74	0	49	0	0.6935	0.2378	0.2287	0.6400	0.1004	0.5132
5	46	98	0	0	0	0.3780	0.5654	0.5381	0.3600	0.4944	0.4545
6	42	89	0	140	0	0.3952	0.5267	0.4929	0.3600	0.4679	0.4531
7	21	78	6	661	0	0.4837	0.4075	0.3777	0.4400	0.3320	0.4482
8	19	79	6	743	0	0.4872	0.4061	0.3775	0.4400	0.3268	0.4470
9	33	99	0	0	0	0.4690	0.4708	0.4550	0.4400	0.3546	0.4321
10	35	99	0	0	0	0.4550	0.4858	0.4683	0.4000	0.3761	0.4301
11	32	97	0	141	0	0.4633	0.4724	0.4542	0.4000	0.3634	0.4300
12	32	100	0	141	0	0.4633	0.4792	0.4636	0.4000	0.3634	0.4275
13	32	100	100	141	0	0.4353	0.5258	0.5501	0.4000	0.3161	0.3835
14	32	100	100	0	0	0.4480	0.5123	0.5372	0.4000	0.2966	0.3815
15	31	100	100	361	0	0.4215	0.5405	0.5640	0.3600	0.3372	0.3814
16	31	100	100	0	0	0.4546	0.5053	0.5306	0.4000	0.2865	0.3808
17	28	100	100	140	0	0.4610	0.4985	0.5241	0.4000	0.2767	0.3802
18	28	100	100	131	0	0.4618	0.4976	0.5233	0.4000	0.2753	0.3802
19	28	100	100	94	0	0.4654	0.4938	0.5197	0.4000	0.2699	0.3800
20	24	100	100	339	0	0.4665	0.4926	0.5185	0.4000	0.2681	0.3799
21	28	100	100	58	0	0.4688	0.4901	0.5162	0.4000	0.2646	0.3798
22	25	100	100	227	0	0.4715	0.4872	0.5135	0.4000	0.2605	0.3797
23	26	100	100	155	0	0.4723	0.4864	0.5127	0.4000	0.2593	0.3797
24	25	100	100	217	0	0.4725	0.4862	0.5125	0.4000	0.2589	0.3797
25	28	100	100	19	0	0.4725	0.4862	0.5124	0.4000	0.2589	0.3796