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***Abstract*— The large-scale introduction of natural energy being promoted worldwide in recent years leads to an increased impact of weather fluctuations on wholesale electricity prices. In markets where the introduction of solar power generation is rapidly progressing worldwide including Japan, hedging needs for revenue fluctuations in the solar power business have been expanding year by year. Therefore, this study proposes hedging strategies for the revenue of power generation companies that trade generated solar power through the wholesale electricity market, using a portfolio of derivatives whose underlying assets consist of fuel price, solar radiation, and temperature. We specifically propose a multilateral hedging method that applies multiple non-parametric regression methods such as tensor product spline function, ANOVA decomposition, and spline function with cross variable, and demonstrate the hedging effect using empirical data from the Japan Electric Power Exchange (JEPX).**

Keywords-component; Non-parametric regression, Minimum variance hedge, Solar power energy, Weather derivatives

I. INTRODUCTION

As part of global warming countermeasures, a large-scale introduction of natural energy is being promoted worldwide. In markets where the introduction of solar power generation is rapidly progressing, such as Japan, the impact of weather fluctuations on electricity prices continues to expand. As a result, hedging needs for revenue fluctuations in the solar power generation business have been expanding year by year. Therefore, this study proposes hedging strategies for the revenue of power generation companies that trade generated solar power through the wholesale power exchange market (e.g., JEPX, PJM, etc.) and verifies the hedging effect using empirical data from the Japanese market.

Weather derivatives are widely used mainly for methods using the temperature index. Previous studies that applied weather derivatives to the electricity industry include proposing a pricing method using trend predictions for futures and options based on the monthly average temperature [1] and proposing weather derivatives for hedging the loss of power prediction errors for either wind power [2] or solar power [3]. Although these studies propose methods for hedging volume risk, such as demand and power output, the hedge methods proposed in [4] also consider price fluctuation risk and hedges the retailer's procurement cost as defined by the product of procurement price (wholesale electricity market price) and demand volume by using temperature derivatives. Another related study [5] verified the cross-hedging effect for a solar power producer in the U.S. when using standard temperature derivatives. This study can be positioned as applied research of [4] for the solar power business in that it proposes a hedging method for the electricity sales revenue defined by the product of wholesale electricity market price and power generation output.

In this paper, to suppress daily fluctuations in electricity sales, we consider building a hedging strategy based on a portfolio of derivatives with crude oil price, solar radiation, and temperature as the underlying assets. This paper also proposes a composite hedging method that applies multiple nonparametric regression methods from different viewpoints, as follows: (1) when estimating the derivatives' payoff function that changes with yearly cyclical trend, we use a tensor product spline function that can take into account the smoothing conditions of both the direction of underlying asset price and time (expiration date) with yearly cyclical trend at the same time; (2) we use a method called ANOVA decomposition to separate deterministic time trends from payoff functions estimated by the tensor product spline functions; and (3) assuming that sales revenue has yearly cyclical trend even when viewed at the rate of annual change, we use a spline function with cross variables to incorporate such mixed effect.

This paper is organized as follows: first, Section II gives an overview of the characteristics of the Japanese electricity market and recent structural changes; second, section III outlines the techniques used in this study; third, section IV formulates a specific hedging model that is treated in this paper; forth, section V examines the hedging effects of derivatives using empirical data; and lastly, section VI provides a summary.

II. RECENT ELECTRICITY MARKET OVERVIEW IN JAPAN

Intended for effective hedge modeling, this section gives an overview of the determinants and the features of electricity prices, in which we describe recent structural changes of the Japanese market. In the following, an analysis is made based on fuel price and supply-demand fluctuations, which are the main determinants of electricity prices.

Relative to fuel prices, the Japanese wholesale electricity price (i.e., JEPX price) is distinguished by its strong link to the crude oil prices in the international oil market. For example, WTI, a typical crude oil price, has been reported to have a substantial correlation with the JEPX spot price, with a time lag of approximately one month [6].

Regarding supply-demand fluctuations, the JEPX price has been declining in recent years due to an increase in the supply capacity of nuclear (subsequent restart after all unit suspension due to the Fukushima nuclear accident) and solar power generation. In particular, solar power generation has continued to increase rapidly since 2012 when a feed-in tariff scheme was implemented; and in 2018, the percentage of solar power in the total national power generation reached 6.5%. Thus, dealing with these annual changes in prices due to the supply-demand structure is also key to constructing an effective hedging model.

III. Minimum variance hedging problem

In this paper, we consider the problem of minimizing the variance of a portfolio consisting of the revenue from selling electricity and the payoff function of the derivatives owned by a solar power operator that enters into a derivative contract through an insurance company in advance.

The payoff function of weather derivatives used in this study is the following. First, the payoff of weather index futures is defined as the realized weather index value minus its predicted value or trend, i.e., the prediction error $\varepsilon_{W,t} := W_t - f_W(t)$ as in [4]. Then, the payoff is given as an arbitrary function $\psi(\varepsilon_{W,n})$ with the prediction error as the underlying asset. As a result, weather index futures that have a definite payoff function are used to find the optimal contract volume; alternatively, weather index derivatives are used to find the optimal payoff function.

A. Estimate smoothing spline function

In this study, as proposed in [2], the generalized additive model (GAM [7]) is used to estimate the optimal future contract amount and the payoff function of derivatives.

1) Optimal contract volume calculation problem

The estimation method of smoothing spline function can be applied to optimal contract volume calculation problems for weather index futures. Specifically, when hedging the fluctuation risk of solar power revenues π_t using weather index futures whose payoff is given by $\varepsilon_{W,t}$, we solve the following minimum variance hedging problem:

$$\min_{\Delta(\cdot), f(\cdot)} \mathrm{Var}\left[\pi_t - f(t) - \Delta(t)\varepsilon_{W,t}\right]. \tag{1}$$

where t is the date and $\Delta(t)$ is the contract volume of the weather futures. Thus, (1) depicts a problem that minimizes the variance of the portfolio consisting of the solar power sales revenue π_t, $f(t)$ unit of discount bonds and $\Delta(t)$ unit of weather futures with payoff $\varepsilon_{W,t}$[2].

2) Optimal payoff function calculation problem

Similarly, the problem of finding the optimal payoff function of a derivative is given by the following:

$$\min_{\psi(\cdot), f(\cdot)} \mathrm{Var}\left[\pi_t - f(t) - \psi(\varepsilon_{W,t})\right] \text{ s.t. } \textstyle\sum_t \psi(\varepsilon_{W,t}) = 0. \tag{2}$$

This equation corresponds to the problem of minimizing the variance of the portfolio composed of electricity sales revenue π_t, $f(t)$ unit of discount bonds, with weather index derivatives with payoff $\psi(\varepsilon_{W,t})$ under smoothing conditions. In this paper, assuming that the payoff function of the derivative is not constant throughout the year but changes smoothly according to the season, we set up the following optimal payoff function calculation problem:

$$\min_{\psi(\cdot)} \mathrm{Var}\left[\pi_t - \psi(t, \varepsilon_{W,t})\right] \text{ s.t. } \textstyle\sum_t \psi(t, \varepsilon_{W,t}) = 0. \tag{3}$$

(3) uses the derivatives payoff $\psi(t, \varepsilon_{W,t})$ as a bivariate function; however, we want to consider an additional condition to obtain a function that smoothly connects both the directions of date t and weather prediction error $\varepsilon_{W,t}$. Here, by estimating the function $\psi(t, \varepsilon_{W,t})$ as a tensor product spline function [8], it is possible to consider such different two-way smoothing conditions simultaneously (See [3] for an example of applying this method to the hedging problem.).

B. ANOVA decomposition

Since the function $\psi(t, \varepsilon_{W,t})$ mentioned above contains a trend related to the date t, there is a problem in that it is difficult to grasp the structure as a hedging model. Therefore, in the following formula, we consider a method of separating the trend for t from the term $\psi(t, \varepsilon_{W,t})$ by applying ANOVA decomposition [9]. When ANOVA decomposition is applied to the function $\psi(t, \varepsilon_{W,t})$, the following equation is obtained:

$$\psi(t, \varepsilon_{W,t}) = \psi_t(t) + \psi_\epsilon(\varepsilon_{W,t}) + \psi_{t\epsilon}(t, \varepsilon_{W,t}). \tag{4}$$

Here, each term on the right side can be found as a function whose average is zero. The univariate spline functions $\psi_t(t)$ and $\psi_\epsilon(\varepsilon_{W,t})$ are called "main effects," and correspond to the trends in which the date or weather index contribute independently to the original tensor product spline functions. Alternatively, the bivariate spline function $\psi_{t\epsilon}(t, \varepsilon_{W,t})$ is called the "interactions effect" and corresponds to the interaction trend of date and weather index, which is obtained by removing the main effects from the original tensor product spline function. At this time, the function $\tilde{\psi}(t, \varepsilon_{W,t}) := \psi_\epsilon(\varepsilon_{W,t}) + \psi_{t\epsilon}(t, \varepsilon_{W,t})$ is obtained as a payoff function of the derivative in which the yearly cyclical deterministic trend is removed from the original tensor product spline function. When this derivative is used, the objective function part of (3) is corrected to the following minimum variance problem (where $\tilde{f}(t) := \psi_t(t)$ is contract unit of discount bonds):

$$\min_{\tilde{f}(\cdot),\tilde{\psi}(\cdot)} \mathrm{Var}\left[\pi_t - \tilde{f}(t) - \tilde{\psi}(t, \varepsilon_{W,t})\right]. \quad (5)$$

IV. CONSTRUCTION OF HEDGING MODELS

A. Model consisting of fuel price and calendar trend

Considering that electricity prices are linked to crude oil prices for large trends as a monthly average and also to day-type and weather conditions in terms of daily granularity, the following "base model" can be constructed:

$$\begin{gathered}\pi_t = \beta \cdot WTI_t + c(t) + \eta_t \\ s.t.\ c(t) := f(t) + f_H(t) I_H(t) + g(t) Period_t.\end{gathered} \quad (6)$$

where π_t is the electricity sales revenue in the spot market on day t ($= \sum_m S_t^{(m)} V_t^{(m)}$, sum of products of spot price $S_t^{(m)}$ and power generation output $V_t^{(m)}$ at each time m), β is the regression coefficient (the contract volume of WTI futures), and WTI_t is the WTI futures price in the previous month of the month to which the day t belongs, $c(t)$ is a calendar trend (the contract unit of discount bonds), and η_t is the residual term with an average of 0. $f(t), f_H(t)$, and $g(t)$ are the yearly cyclical trends estimated by GAM[1], while $I_H(t)$ is a dummy variable that is 1 if the day t is Saturday, Sunday, or holiday, and 0 otherwise. $Period_t$ is the t th day's elapsed years (not necessarily an integer) from the beginning of the data starting year[2]. Of these, the term $g(t)Period_t$ is introduced assuming that the calendar trend has yearly cyclical trend even when viewed at the rate of annual change, and $g(t)$ means the cyclical trend of the annual change. $g(t)$, as a spline function with cross variables, can be obtained as a quadratic programming problem and estimated by the same means as normal GAM [4].

Note that η_t indicates the hedge error. Estimating the regression coefficient and spline functions using GAM (6) corresponds to solving the hedging problem for the unit of holding WTI futures and discount bonds that minimizes the residual sum of squares of the hedging error $\mathrm{Var}[\eta_t]$.

B. Model using solar radiation futures

Next, assuming the case where solar radiation futures can be used, we consider the following hedging model:

$$\pi_t = \beta \cdot WTI_t + c(t) + \gamma_1(t)\varepsilon_{R,t} + \eta_t. \quad (7)$$

where $\varepsilon_{R,t}$ is the solar futures payoff (solar prediction error) on day t, and $\gamma_1(t)$ is the yearly cyclical trend of the solar futures' contract volume.

As shown in section II, due to an increase in solar power generation, the sensitivity of power sales revenue to the solar prediction error (contract volume of solar futures) is assumed to have a yearly cyclical annual change trend. Considering this point, the following model can be constructed:

$$\begin{gathered}\pi_t = \beta \cdot WTI_t + c(t) + \gamma_1(t)\varepsilon_{R,t} \\ +\gamma_2(t) l(Period_t)\varepsilon_{R,t} + \eta_t.\end{gathered} \quad (8)$$

Here, among the fourth term, we define $l(Period_t)$ in advance as $1 - exp[-Period_t]$, a nonlinear ageing trend function (a monotonically increasing decay function).

C. Model using temperature derivatives

Similarly, a hedging model using temperature derivatives is as follows:

$$\pi_t = \beta \cdot WTI_t + c(t) + \widetilde{\tau_{te}}(t, \varepsilon_{T,t}) + \eta_t. \quad (9)$$

where $\varepsilon_{T,t}$ is the temperature prediction error on day t and $\widetilde{\tau_{te}}(t, \varepsilon_{T,t})$ is the payoff function of a temperature derivative estimated as a tensor product spline function from which a definite yearly cyclical trend has been removed by ANOVA decomposition in the way described in section III.

V. EMPIRICAL ANALYSIS

In this section, we verify the effectiveness of the proposed method using real data as follows:

(a) Electricity spot price S_t [JPY/kWh]: JEPX area price of Chugoku where Hiroshima city is located[3]

(b) Solar power output volume V_t [kWh]: measured value of household's solar power system in Hiroshima city[4]

(c) Solar radiation R_t[J/m^2], Max temperature T_t [℃]: realized value of Hiroshima city published by Japan Meteorological Agency[5]

(d) WTI crude oil price WTI_t [Thousand JPY/bbl]: historical WTI spot price FOB[6]

A. Trend estimation of hedge models

In this subsection, we estimate the model parameters and the trend functions using data for five years from January 1, 2013 to December 31, 2017 and consider the results.

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[1] We estimate the yearly cyclical trend using the smoothing spline function $f(Seasonal_t)$ with yearly cyclical dummy variables $Seasonal_t$ ($= 1, \ldots, 365(or\ 366)$), whose allocation method is proposed in [10]. In this work, the starting point of the cyclical dummy variables is January 1, and from 1 to 365 (366 for leap years) are allocated in order. Note that we denote $f(Seasonal_t)$ as $f(t)$ for concise notation.

[2] $Period_t$ is defined as a dummy variable calculated by the following equation: $Period_t := Year_t - Year_1 + Seasonal_t / Days_t$, where $Year_t$ is the year to which the t th day belongs, and $Days_t$ is the total number of days in the year to which the t th day belongs.

[3] Downloaded from http://www.jepx.org/market/index.html.

[4] With the permission of the owner, we use the data of the private roof-mounted power system in Hiroshima city.

[5] Downloaded from https://www.data.jma.go.jp/gmd/risk/obsdl. Note that considering the correlation with the JEPX Chugoku area price, the max temperature data is created by averaging the temperatures in Nagoya City, Osaka City, and Hiroshima City by weighting the total prefecture population in which each city is located.

[6] Downloaded from https://www.eia.gov/dnav/pet/hist/RWTCD.htm. Note that it is converted into JPY using the past exchange rate published by the Bank of Japan (downloaded from https://www.stat-search.boj.or.jp/).

1) Optimal contract volume of solar radiation futures

First, we consider the estimation results of model (8) on solar radiation futures. The Figure 1. shows a composite calendar trend $f(t) + g(t)Period_t$(displayed range of t axis is from Jan. 1 to Dec. 31). In 2013, the peak power sales revenue was around May; however, the peak in 2017 has moved to around August because an increase in solar power facilities has led the JEPX price to decline particularly in May when the amount of solar radiation is increased in the year.

Next, the estimation result of the solar radiation future contract amount $\gamma_1(t) + \gamma_2(t)l(Period_t)$ in model (8) is shown on the Figure 2. This trend corresponds to the sensitivity of power sales revenue to the solar radiation residual. As this estimate shows, the rate of annual change varies greatly depending on the season.

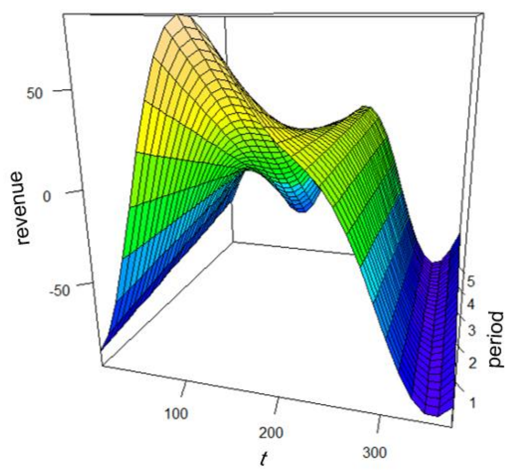

Figure 1. Estimated calendar trend in model (8)

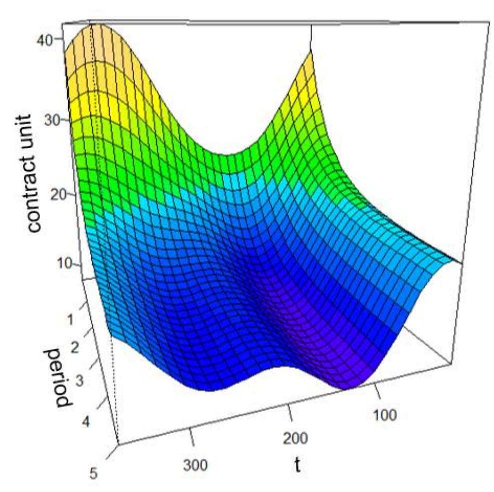

Figure 2. Estimated solar radiation futures optimal contract amount in model (8)

2) Optimal payoff function of temperature derivatives

Figure 3. shows the estimated result of the temperature derivative payoff function $\widetilde{\tau_{te}}(t, \varepsilon_{T,t})$, which is defined as a tensor product spline function using ANOVA decomposition in the model (9).

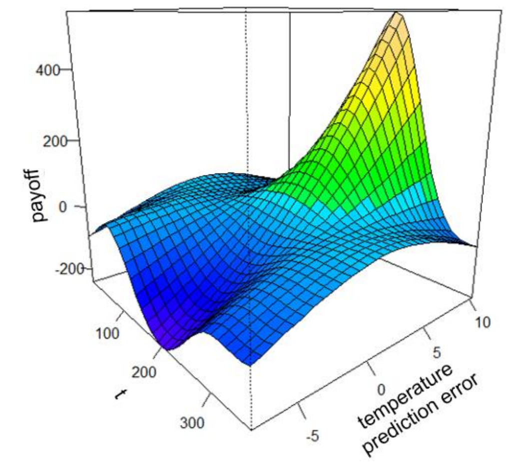

Figure 3. Payoff function for temperature derivatives in model (9)

It has been confirmed that the sensitivity (slope) of solar power revenue to the temperature residual significantly increases in summer. It is thought that the rise in temperature in summer affects both the increases in power output and price (due to increase of power demand).

B. Measurement of hedge effects

Next, using the parameters and functions estimated from the learning period data (from January 1, 2013 to December 31, 2017), we calculate the hedge effect of the weather derivative during the simulation period (from January 1, 2018 to December 31, 2018). In this study, we define the variance reduction rate (VRR) as follows and call 1-VRR the hedge effect:

$$\text{VRR} := \frac{\text{Var[hedge error of the target model]}}{\text{Var[hedge error of the base model]}}. \qquad (10)$$

Here, we analyze changes in hedge effects when each derivative (hedge model term) is combined cumulatively. Figure 4. shows the contribution rate when each derivative is used alone (bar graph), the cumulative contribution rate when the terms are combined in order from the top (blue line graph), and the cumulative hedging effect of the weather derivative compared to the base model (6) (red line graph)[7].

[7] Note that the items (numbers) in Figure 4. correspond to the following terms in the hedge model formula: 1. $f(t)$, 2. $f(t) + f_H(t)I_H(t)$, 3. $g(t)Period_t$, 4. $c(t)$, 5. WTI_t, 6. $\gamma_1(t)\varepsilon_{R,t}$, 7. $\{\gamma_1(t) + \gamma_2(t)l(Period_t)\}\varepsilon_{R,t}$, 8. $\widetilde{\gamma_{te}}(t, \varepsilon_{R,t})$, 9. $\gamma_2(t)l(Period_t)\varepsilon_{R,t} + \widetilde{\gamma_{te}}(t, \varepsilon_{R,t})$, 10. $\tau(t)\varepsilon_{T,t}$, 11. $\widetilde{\tau_{te}}(t, \varepsilon_{T,t})$.

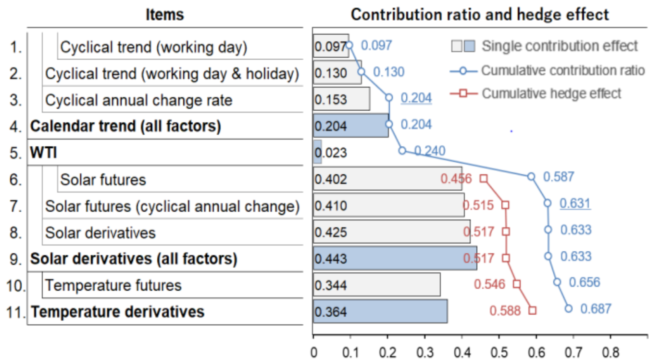

Figure 4. Cumulative contribution ratio and hedging effect of solar radiation and temperature derivatives

First, it was confirmed that the highest two contribution rates are solar derivatives and temperature derivatives. Next, looking at the cumulative contribution rate, a significant improvement was observed by adding yearly cyclical trends of annual change to the calendar trend or the solar radiation future contract amount. The former is improved by 7% and the latter by 4% (underlined). Also, the cumulative contribution rate increased monotonously with the inclusion of each term and reached 0.687 when all were combined.

Finally, regarding the cumulative hedging effect, that of the solar radiation derivative was 0.517, and it improved to 0.588 when combined with the temperature derivative. Although not shown in the figure, even when using only temperature derivatives, a sufficient cross-hedging effect of 0.300 was obtained. As for the hedging related to temperature, it is interesting that the hedging effect is greatly improved by using derivatives given by nonlinear payoff functions instead of using futures with a linear payoff function. Compared to the hedging effect when using only solar radiation derivatives (0.517), there was an improvement of 3% when combined with temperature futures (0.546) and an improvement of 7% when combined with temperature derivatives (0.588).

VI. CONCLUSION

In this paper, we proposed a hedging method using derivatives related to solar radiation and temperature against the fluctuation of solar power sales revenue and measured the hedge effects using Japanese data. The proposed method is based on the concept of the existing method for the retailer's procurement cost but includes the following new points:

- We set up a problem of finding the payoff function of nonlinear derivatives that change with the season and apply the tensor product spline function to estimate it
- By using ANOVA decomposition, we make it easier to capture the structure of the hedge model
- We assume that sales revenue has seasonality even when viewed at the rate of annual change and use a spline function with cross variables to estimate this trend

For solar power sales revenues, the solar radiation derivatives provide a hedging effect that reduces the original variance by about 52%, and the combined use of temperature derivatives enables improvement to about 59%. Furthermore, there was a hedging effect of about 30% even when only temperature derivatives were used. The hedging strategies proposed in this study may be further developed for practical use in the near future as the introduction of renewable energy is continuously increasing.

In order to show more universal effectiveness, it is a future task to verify using the verification results of empirical data from several cities and make analyses of these verification results.

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