Project Proposal_tl7fha

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Title: Demand-side Management of Smart Appliance Based on Optimization Prediction Tools
Subtitle: Project proposal for University of Virginia SYS 6014 Decision Analysis Spring 2020
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Summary
Demand-side management is one the approach that can be applied to save the cost of energy for both individual's and world's benefit.
If we can allocate electricity to smart appliance according to current flowing price, we can make great benefits.
In this scenario, we will be using the forecast electricity price data as our basis to predict the realized price. We will use historic real-time and forecast price data to generalize a model that can fit both data. Then we can predict the realized price one-day ahead according to the day-ahead predicted data. The result of the real-time updated data will be used to refine the model.
Based on that predicted realized price value and the given working hour range, we can find the optimal working time for the smart appliance.

The source of data:
https://www.nyiso.com/

Data we have:
Forecast electricity price data: every hour's LBMP based on forecast everyday(locational based marginal pricing) .
Historic real-time electricity price data: real-world recorded LBMP every 5 minutes everyday(continuously updating to today).

The decision problem:
The decision-maker should be the smart appliance itself, to decide which time to start doing the job in order to get the lowest cost of electricity based on predicted realized LBMP in a typical day. The analysis here uses statistical decision theory to generate a recommendation about which time to start working, in order to get a best potential price to save money.

Formalism
The decision maker's action set $\mathbb{A}$: choose a starting working time (certain hour to start working) to complete the job. a_h: binary control variable; a_h=1 if choose to start working from hour h. 0 otherwise.
a=<a_{H-L} ...,a_1>: actions chosen on hours h= H-L,...,1

Parameters we will have here
H: length of the given working time range
L$\leq$H working hours needed to complete the work
$h \in$ (1 , H): index of total available working hours

$l \in$ (1 , H-L): index of left available starting working hours
Y=<Y_H $Y_H - 1$ ...,Y_1>: price on hours h= H,...,1
$X1_h$: variable indicating realized value of historic predicted electricity price.
$Y1_h$: variable indicating realized value of historic real-time electricity price.
$X2_h$: variable indicating realized value of day-ahead predicted electricity price.
Y_h: random state variable indicating realized value of electricity price.

Payoffs: The loss function
Let $L(a, y)$ denote the losses incurred by electricity usage by smart appliance. $L(a, y)$=$\sum_h^{h+L}$E[Y]

Uncertainty
Arrangements to arrange working time for smart appliance according to the predicted price data one day ahead before the real price is known. Let Y denote the random electricity price.

Decision criterion
The decision criterion for smart appliance is: choose the start working hour that minimizes losses in expectation:

$$a^* = \operatorname*{argmin}_{a \in \mathbb{A}} E[L(a, Y)]$$

where the expectation is taken over the distribution of Y. This distribution represents the information about uncertain electricity price we can predict using the predicted price data for smart appliance to make decision to work.

Data generating process
We will use the historic data$X1_h$ and $Y1_h$) collected from the website(both predicted price and real-time price) to build a linear model to make prediction about the realized price(get distribution of Y_h) distribution given new day-ahead predicted price($X2_h$).
The process can be concluded as follows: historic predicted price($X1_h$) + historic real-time price($Y1_h$) + –> linear model and error distribution($Y1_h$= β_0 + $\beta_1 X1_h$ + ε_i) –>given the day-ahead predicted price($X2_h$) –> predict the distribution of the realized price(Y_h).
That is, given a new predicted price data by the website one day ahead, we will have a prediction about the distribution of the realized price. We will use the mean value of every 5 minutes' real-time price within each hour to represent the every hour's real-time price($Y1_h$). And to match it with the predicted every hour's price($X1_h$) in the same location to build the model. After getting the real-time price data of the new day, we will fit it into the model to get better results for the future(make calibration).

The parameter space: The set of possible values for the unobserved parameter θ. $\theta, \sigma_1 \in \mathbb{R}X(0, \infty)$. In this case, we represent the randomness of unobserved thing as the error distribution of the linear model we build (the fluctuation of price).

The decision-maker's prior beliefs: Generally speaking, all price data $X \in$ (0 , 30), working length $L \in$ (0 , 24) and L should be an integer. We will know about the working time of the appliance(needed time for working). And we will know the location and working time range.

The process for getting better information:
We will use real-time price data to update(calibrate) our prediction model to make sure that we can have better price for this decision-making process to save money for the owners. We can approach optimal choice for the smart appliance to work step by step.

The rule the decision-maker will use to choose a preferred action:
Set the working time range according to their preference.

Some assumptions we have for our model:
1.It is supposed that there is a linear relationship between predicted price and real-time price.
2.The error term ε_i follows a normal distribution: $\varepsilon_i \sim N(0, \sigma_\varepsilon^2)$.
3.The process is assumed to be stationary. There is trend over time and months, years.