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# Risk-constrained framework for residential storage space heating load management

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ABSTRACT

Residential demand response based on real time pricing provides a strong incentive for customers to reduce their energy payment. However, acting under an environment with time-varying prices will expose them to uncertain energy bills. This paper presents a risk-constrained framework for residential customers for scheduling the electric storage space heating load. The proposed decision framework attempts to accomplish desired settlement between expected cost minimization and cost deviation without altering the user's thermal comfort. The price and load uncertainty are captured by a scenario based stochastic programming approach. The optimization model is solved using Genetic Algorithm and implemented using a moving-window procedure. The simulation results demonstrate that the proposed framework for scheduling the storage space heating load provides a method to selectively hedge against the price and load uncertainty risk. The optimal framework will result in an improved interaction between the electrical aggregator and its customers under the smart grid paradigm.



## 1. Introduction

### 1.1. Motivation

In today's power system, safe integration of intermittent renewable energy resources is considered to be the most demanding challenge. Problems that further aggravated the situation include charging electric vehicles, aging infrastructure and institutional changes in electricity markets. In these circumstances, demand response is seen as one of the effective tools for alleviating these issues [1–3]. Demand response is a mechanism to motivate the customers, by either changing prices or giving incentives, to adjust the electricity consumption to bring favorable results for power system operation at different time-scales. Real time price (RTP) based demand response is considered to be the most effective mechanism for demand side management (DSM) [4]. Future smart grids can enable demand side management, integration of distributed energy resources and improve power system efficiency [5]. With the advent of smart grid technologies, the real time interaction between customers and electrical aggregators is becoming possible and a household customer can also participate in demand response programs implicitly optimizing the power system operations [6].

Amongst the household loads, the thermostatic controlled appliances (TCAs) such as electric space heaters, electric water heaters, fridge, etc are logically the most suited load for an effective demand response application. The time postponement and power-schedulable characteristic of the TCAs load qualifies it as a well-suited load for DSM programs from an electrical aggregator perspective. The flexibility of TCAs is enhanced if it is equipped with some degree of thermal energy storage. For instance, equipping space heating system with thermal storage (system commonly known as electric storage space heating, see Fig. 1) allows heating to uncouple from the system hence the power interruption can take place with almost no impact on customer's thermal comfort and can be used for power system operation optimization.

At present, many electric storage space heating consumers are charged according to the static Time of Day distribution tariffs despite considerable hourly variation in the wholesale market power price. The existing Time of Use (ToU) tariff help the household consumers to manage their heat consumption by charging the thermal storage during night time and then allowing the stored heat to coast through the rest of the day. Nowadays, with the advent of smart meters and the penetration of intermittent renewable generation, a contractual agreement between

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**Nomenclature**

| | |
|---|---|
| $\beta^r$ | risk coefficient |
| $C^e$ | electricity price (€/kWh) |
| $D^l$ | maximum power taken from the electric storage space heating system (kW) |
| $N$ | total number of scenarios considered. |
| $P^{ch}$ | charging power (kWh/h) |
| $P^d$ | direct electric heating power (kWh/h) |
| $Q$ | power taken from thermal storage (kWh/h) |
| $q_{h,n}$ | average heat demand (kWh) during hour $h$ and scenario $n$. |
| $S_0^t$ | initial level of thermal storage (kWh) |
| $SL_h^t$ | stored energy lost during hour $h$ (kWh) |
| $S_{max}^t$ | net storage capacity (kWh) |
| $Z^N$ | expected cost over $N$ scenarios (€) |
| $\Omega(n)$ | probability of scenario $n$ |
| $\gamma$ | storage loss coefficient |
| $FR$ | financial risk |
| $h$ | index of hours |
| $n$ | index of scenarios |

the end consumers and electrical aggregator can be made possible so that the customers can respond to more dynamic time varying prices. One of the serious implications of such a demand response program is that it could expose the end-user to the financial risk especially if the power prices are highly volatile [7,8]. A comprehensive report [9] by US department of energy on utility experience with real-time pricing suggest that RTP can be an attractive tariff however there are potential risk burdens associated with that which must be overcome in order to encourage the extent of customers participation in real-time demand response programs. Although a very attractive pricing scheme, the RTP prices can subject the consumers to a relatively high degree of risk by exposing them to stochastic power prices [9].

### *1.2. Approach*

In an attempt to offset the customer's potential risk that may be incurred due to the price volatility and load uncertainty as well as simultaneously reducing the energy payment, we present an optimal framework for scheduling the electric storage space heating load. The uncertainty is modeled using a scenario based stochastic programming approach. The proposed demand response model adequately considers the risk-level while reducing the expected energy cost of the customer. The risk is simply modeled by the minimum variance approach. Moreover, the customer's thermal comfort is not compromised as the proposed demand response model manages the thermal storage operation without compromising on the energy demand during that hour. The decisions are made for next 24 h but executed and revised on an hourly level (the approach commonly known as a moving window procedure) as the new information on prices and demands are updated on an hourly basis.

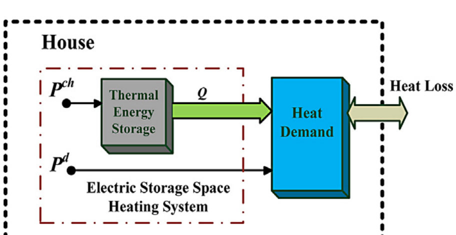


**Fig. 1.** Illustration of a typical electric storage space heating system. In this figure, the sum of $P^{ch}$ (charging power) and $P^d$ (direct heating power) is the total thermal power output of the storage space heater.

### *1.3. Related work and contribution*

A significant amount of research studies have concentrated on the residential demand response. The most relevant works are reviewed in the following to demonstrate the contribution of this paper. The authors of [10] presented an optimal operation of major residential load under a smart grid scenario. The work in [11] presented an optimal energy scheduling framework for an automatically operating appliance. A co-evolutionary particle swarm optimization (PSO) based decision support tool for optimally scheduling distributed energy sources at household level is developed by Angelo et al. [12]. Rad et al. [13] formulated an optimal household load control under a real-time pricing and inclining block rate environment to achieve a tradeoff between energy payment and waiting time. Peizhong et al. [14] proposed a scheduling scheme based on optimal stopping rules to achieve the same objective. A robust optimization model to schedule the hourly-level consumption is developed by Conejo et al. [15]. In [16], an appliance commitment algorithm that schedules thermostatically controlled appliances considering user comfort under the price and demand uncertainty situation. A Markov decision framework to schedule the power consumption based on future price forecasts was discussed by Kim and Poor [17]. An efficient scheduling algorithm to optimize the household appliance operation considering demand and intermittent renewable uncertainty was proposed in [18]. In [19], a study has been performed to assess the domestic demand response potential of responsive appliances. The work [20] proposed a distributed algorithm solution for unleashing domestic demand response in smart grid environment. The research in [21] coordinated the load management of heating load and electric vehicles to bring customer economic savings. The demand response model evaluates the cost of discomfort and temperature preferences however the framework does not account the uncertainty and risk issues. The work [22] demonstrated the performance of dynamic controller for residential building demand response application. Some studies have principally focused on the demand response control of a particular flexible appliance such as water heater [23], electric vehicle [24], and freezer [25] to name just a few.

Most of the above reviewed work focused on customer load scheduling in order to minimize the user energy payment under dynamic prices. However, despite its importance, the customer's financial risk associated with electricity purchasing under RTP were not adequately discussed in the literature. Nonetheless, there exist a few papers that addressed the problem from the perspective of a risk-averse energy retailer [26–28]. A few risk measures were described and used in these papers which can be useful in the current study as well as the future works, however, more comprehensive models are required to be provided to achieve the ultimate benefits of demand response potentials.

In this regard, this paper develops a risk constrained model to minimize the expense of heating demand for a residential customer. The core contributions of this paper may be summarized as follows:

- It presents a user-eccentric tool for customers to optimize their space heating load under uncertainty environment without deteriorating the customer's thermal comfort.
- To minimize customer's cost at a given risk level, a non-linear optimization problem is formulated to obtain the optimal amount