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Stochastic Filtering Methods for Predicting Agent Performance in the Smart Grid

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Abstract. A variety of multiagent systems methods has been proposed for forming cooperatives of interconnected agents representing electricity producers or consumers in the Smart Grid. One major problem that arises in this domain is assessing participating agents uncertainty, and correctly predicting their future behaviour. In this paper, we adopt two stochastic filtering techniques —the Unscented Kalman Filter equipped with Gaussian Processes, and the Histogram Filter— and use these to effectively monitor the trustworthiness of agent statements regarding their final actions. The methods are incorporated within a directly applicable scheme for providing electricity demand management services. Simulation results confirm that these techniques provide tangible benefits regarding enhanced consumption reduction performance, and increased financial gains.

1 Introduction

Smart Grid-related research has received much attention in the last few years. Its general objective is to create a more secure, reliable and efficient electricity networks infrastructure, with affordable energy produced mostly by green sources, production costs minimized, and energy savings maximized [5]. Due to the scale and complexity of electrical networks management, artificial intelligence (AI) and multiagent systems (MAS) solutions are in high demand in the emerging markets involving business entities providing services in the Smart Grid [9]. Many such entities have already adopted a business model that pulls together the resources and abilities of multiple economically-minded individuals. For instance, the emergence of *Virtual Power Plants* or *cooperatives* of small-to-medium size electricity producers or consumers has been hailed as a means to create large and trustworthy providers of renewable energy production or electricity consumption reduction services [1, 4, 10, 9]. Generally, instead of peak-trimming, recent work has shown that it may be more appropriate to balance demand according to production of electricity and *proactively* avert the creation of peaks [1, 3].

In this work, we adopt the approach of [1], for *collective power consumption shifting* provided by electricity consumer cooperatives. For shifting coalitions to be effective, members are required to state to the cooperative *(a)* their estimated reduction capabilities, and *(b)* their confidence on the accuracy of that estimate. Although agents are motivated to be truthful via the employment of the *Continuously Ranked Probability Score (CRPS)*, such "fines" might scare agents and keep them away from participation. Also, even if participating agents are perfectly truthful regarding their abilities and corresponding uncertainty, their reports and estimates can still be highly inaccurate — e.g. due to communication problems, malfunctioning equipment, or prejudiced beliefs and private assumptions. Thus, monitoring the performance of individuals and correctly predicting their future contributing potential is of utmost importance to the cooperative.

To this end, several approaches try to explicitly estimate agent electricity consumption and production amounts, by incorporating prediction models that rely on agent geographical location and weather forecasts, or the processing of macroeconomic data [6, 8]. This paper proposes the application of generic prediction methods, which are nevertheless able to adapt to a specific agent's behavior and generate accurate estimates. More specifically, we propose the use of *stochastic filtering methods* to keep track of the parameters that best describe agent behavior, and effectively estimate actual future agent performance. These techniques are able to not only fit the dynamics of the processes governing agent performance, but can also imbibe the potential errors of electricity metering or information transmission devices. In particular, we adopt the *Histogram Filter (HF)* [11] and the *Unscented Kalman* filter (UKF) equipped with a *Gaussian Process (GP)* [2, 7] to predict the future actual actions of agents participating in cooperatives offering electricity DSM services.

2 Electricity Demand Shifting

In this section, we describe the features of the approach of [1] which we monitor and try to predict, in order to enhance the performance of electricity consumer cooperatives taking part in *collective power consumption shifting* operations. For the cooperative to place a bid, each contributing agent i must state its reduction capacity, $\hat{r}_i^{t_h}$, at t_h high-consumption (peak) intervals, and corresponding shifting costs for moving consumption to non-peak, t_l, intervals. Agents are also required to state their uncertainty over their *expected relative error* regarding their $\hat{r}_i^{t_h}$, in a form of a normal distribution $\mathcal{N}(\mu_i, \hat{\sigma}_i^2)$. Next, the cooperative assigns a *conservative* estimate of each agent's performance (but still *"trusts"* the reported $\hat{\sigma}_i$):

$$\tilde{r}_i^{t_h} = (1 - \hat{\sigma}_i)\hat{r}_i^{t_h} \tag{1}$$

Then, the agent's *reservation price* (that is, the highest price i is willing to pay for shifting consumption from t_h to t_l without suffering a monetary loss), is calculated; and so is the agent's *contribution potential*, the product of the expected reduction and reservation price, $\tilde{r}_i^{t_h}\hat{p}_i$. The agents are then ranked by descending contribution potential, and *shifting coalitions* are formed by the number of top agents that meet the required constraints. Selected coalitions are awarded low, *variable prices* for shifting to t_l, determined by a *group price* $p_g \leq p_l$ which is guaranteed by the Grid, and by monetary *transfers* that make it worthwhile for everyone selected to participate [1].

It is obvious that the expected coalition performance is greatly affected by agent statements, which, if inaccurate, endanger the

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scheme's stability and effectiveness. This is why a *trusted index* r^*_{i,t_h} is needed—one not stated explicitly by i, but nevertheless revealing the distribution best describing future agent actions. This index can then be used instead of $\tilde{r}_i^{t_h}$ to calculate a more accurate *contribution potential* for i. To explain further, $r_i^{t_h}$ is the actual amount of load reduced, and which can be, in general, assumed to be provided by a transformation (unknown at this point) of the stated reduction capacity $\hat{r}_i^{t_h}$ of agent i: $r_i^{t_h} = \alpha_i \cdot \hat{r}_i^{t_h}$, with α_i corresponding to a random variable following some unknown probability distribution.

Our objective is to build models for agent performances by approximating the distributions α_is follow. We then sample such a distribution to obtain a better α_i estimate, denoted $\tilde{\alpha}_i$; and use it in order to calculate our trusted index r^*_{i,t_h}, with which we replace $\tilde{r}_i^{t_h}$:

$$r^*_{i,t_h} = \tilde{\alpha}_i \cdot \hat{r}_i^{t_h} \tag{2}$$

Thus, more accurate predictions about individual agent and cooperative electricity consumption shifting abilities can be obtained.

3 Method Description

Given all underlying uncertainty, agents' final behaviors most likely correspond to complex, non-linear functions of past behavior. Therefore, we chose to test two filtering approaches that are expected to fit such a function well: *(a)* a non-linear *KF* approach, the *Unscented Kalman Filter (UKF)* equipped with a *Gaussian Process (GP)*; and *(b)* the *Histogram Filter (HF)*, a non-parametric filtering technique.

Unscented Kalman Filter with Gaussian Process The classic *KF* algorithm is limited to systems with linear transition and observation models; while the *EKF* can handle non-linearities, but not in an optimal manner [11]. The *UKF*, uses the *unscented transform* to obtain better estimates when dealing with non-linear models [12]—such as those that may describe consumption shifting capabilities.

Let $\mathbf{x} \in \mathbb{R}^L$ be a Gaussian random variable with mean $\bar{x}$ and covariance $\mathbf{P_x}$ that is propagated through a nonlinear function $\mathbf{y} = g(\mathbf{x})$. A matrix $\mathcal{X}$ can be constructed that contains $2L+1$ *sigma vectors* $\mathcal{X}_j$ and their corresponding weights W_j, via the *unscented transform* procedure. Next, the *sigma vectors* are propagated via a nonlinear function $\mathcal{Y}_j$. Then, the mean and covariance of $\mathbf{y}$ are approximated by a weighted sample mean and covariance of the posterior *sigma vectors* [7]. In our setting, $\mathbf{x}$'s are $\hat{\sigma}_i$'s, and $\mathbf{y}$'s the estimates about the final α_i. Now, when an agent states an uncertainty forecast $\hat{\sigma}_i$, the expected mean and variance of the corresponding α_i are given by a GP that has been trained on past $\mathcal{D} = (\hat{\sigma}_i, \alpha_i)$ pairs.

So, the final model can be summarized as:

$$\sigma_\tau = A\hat{\sigma}_i + w_\tau \tag{3a}$$

$$\alpha_\tau = GP_\mu(\sigma_\tau, \mathcal{D}) + u_\tau \tag{3b}$$

with noise u_τ following $\mathcal{N}(0, GP_\sigma(\sigma_\tau, \mathcal{D}))$. By using this approach, α_τ's converge to some value $\tilde{\alpha}_i$ that represents the more accurate estimate of the actual α_i. Due to lack of real data about the transition model, and for the fairness of comparison with the HF below, we set A to be I; and w_τ is assumed to follow $\mathcal{N}(0,1)$.

Histogram Filter Histogram filters (HF) decompose a continuous state space to a finite set of areas or bins, that are a partition of the initial space. Then, a probability p_k is mapped to each bin, whose value depends on the frequency of the observations in the range of that bin. With this approach, agent forecasts $\hat{\sigma}_i$s are completely ignored, and only past observations of α_i are taken into account.

4 Experimental Evaluation

In a first set of experiments, we define three classes of agents: the *accurate predictors* (who almost always act as they predicted), the inaccurate predictors (who usually are off their predictions by 50%), and the uncertain predictors (who might or might not follow their stated forecasts). Agent behaviour is simulated by sampling appropriate Beta and Gaussian distributions, which generate the required α_is and $\hat{\sigma}_i$s. In order to rank the classes above, we employ three methods: *Conservative Trusting (CT)*, the method used in [1]; *HF*, which utilizes a *Histogram Filter* constructed by past α_i observations and does *not* take into account $\hat{\sigma}_i$ statements; and *GP-UKF* which also keeps track of past observations, but takes into account $\hat{\sigma}_i$ statements. Our simulations show that *GP-UKF* outperforms *HF* and *CT*, both in terms of absolute relative error mean and variance. When dealing with *accurate predictors*, there is no big performance difference. However, when monitoring *inaccurate predictors*, the *HF* and *GP-UKF* methods capture the systematic inaccuracies of agents and perform very well, while the *CT* does not. Moreover, in additional tests, the *CT* method performs far worse than the others.

In a second experimental setting, we applied our proposed methods to the scenario of [1], considering cooperative consumption shifting efforts over a 10-day period (using simulated data originating from a real-world dataset). In this setting, *GP-UKF* achieves reduction that is closer to the expected compared against the other methods. It thus manages to perform better in terms of economic benefits also, generating more actual gain in euros than any other method. Specifically, the *CT* method achieves 28241.193 KWh of actual reduction, as opposed to an expected reduction of 35928.151 KWh; while the amounts for *HF* are 30249.181 KWh and 36073.986 KWh, and for *GP-UKF* 35236.2815 KWh and 36182.952 KWh respectively. In terms of actual gains, the methods rank as follows: *CT*: €1199.9, *HF*: €1447.55, *GP-UKF*: €1987.22.

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