Poster Abstract: Towards Battery-Free Short-Term Energy Prediction with Regime Learning

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***Abstract*—Battery-free devices harvest energy from the environment and use tiny capacitors as energy storage. As ambient energy sources are often considered unpredictable, battery-free systems typically manage energy in a dynamic and reactive way. We propose to complement these strategies with a proactive approach by learning harvesting regimes using an Autoregressive Hidden Markov Model (AR-HMM). We show that by applying certain environment-agnostic transformations to energy sources, it is possible to extract locally predictable dynamics using lightweight models with few trainable parameters. We conduct simulations under multiple configurations and demonstrate that the AR-HMM combined with a Stationary Wavelet Transform (SWT) effectively models several relevant energy environments.**

***Index Terms*—battery-free, energy harvesting, energy prediction, hidden Markov model, time series processing**

I. Motivation

While the absence of a battery reduces the economic and environmental cost of embedded systems, it also introduces a strong dependence on energy source fluctuations, leading to a risk of power failures. In the literature, energy harvesting in battery-free systems is often considered stochastic, non-linear, and difficult to predict [1] [2]. Energy management is therefore generally carried out in a reactive manner, using approaches such as *intermittent computing* or *checkpointing*. However, the harvested power signal exhibits periodicities and local trends, which suggest the presence of regular, linear, and predictable behaviors [3]. These could potentially be exploited to make more informed energy management decisions based on short-term energy predictions.

In the absence of expert knowledge, the diversity of energy environments requires prediction systems to learn the dynamics of their sources. While some non-linear machine learning models show good results for short-term energy prediction, their computational cost prevents deployment on resource-constrained embedded devices [4]. Conversely, lighter linear models poorly capture non-linearities, limiting their accuracy.

We introduce the notion of *regime*, defined as a temporal state during which the dynamics of the energy environment can be modeled linearly within a suitable representation space.

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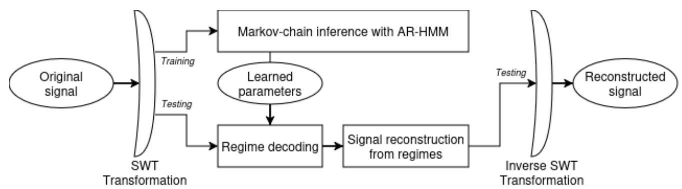

Fig. 1. Regime learning framework.

By applying this approach, non-linear behavior can thus be modeled solely using linear models with few parameters.

II. Methodology

We assess the quality of a regime decomposition through two factors:

- **Reconstructibility**: knowledge of the regimes should allow the reconstruction of a signal similar to the original.
- **Persistence**: the longer the regimes, the more predictions can be made over a long time horizon.

We propose to learn the characteristics of individual regimes and the transitions between them using an Autoregressive Hidden Markov Model (AR-HMM). AR-HMM infers the parameters of a latent Markov chain, where each state is associated with an autoregressive model [5]. In our case, a Markov state corresponds to a regime. The parameters are estimated from a sequence of observations: namely, the harvested power measurements at each time t, which are mapped into another representation space. Observation equation is given by:

$$y_t = \sum_{i=1}^{p} \phi_{s_t}^{(i)} y_{t-i} + \epsilon_t \tag{1}$$

where y_t is an observation, s_t is a hidden state (regime), ϕ_{s_t} is the matrix of inferred coefficients, p is the model order, and ϵ_t is a white Gaussian noise with parameters $(0, \sigma_{s_t}^2)$. Learning is performed with the Expectation-Maximization algorithm, and the number of states in the chain is a hyperparameter.

We propose representing the harvested power in the time-frequency domain by applying a Stationary Wavelet Transform (SWT), which is based on an undecimated wavelet decomposition [6]. Once the model is trained, each new observation is classified by decoding the most probable regime using *forward filtering*, which allows real-time decoding (see Fig. 1).

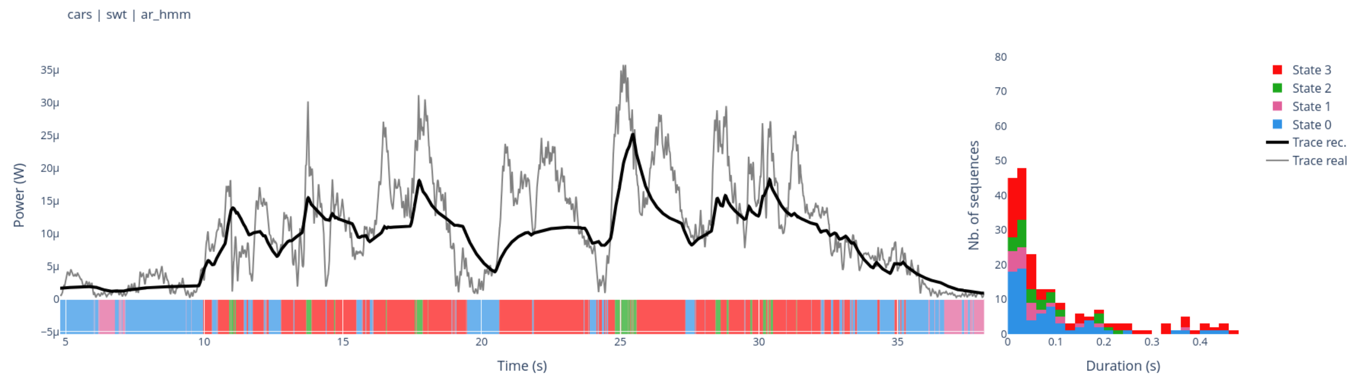

Fig. 2. Experimental results for the Car dataset with AR-HMM and SWT. In black: reconstructed trace. In gray: real trace. In color: regimes. On the right: distributions of observation sequences within the same regime.

TABLE I
EXPERIMENTAL RESULTS.

		Jogging		Washer		Car	
		R^2	P	R^2	P	R^2	P
AR	Raw	-0.051	-	-0.009	-	-0.413	-
	SWT	-0.041	-	-0.014	-	-0.142	-
AR-HMM	Raw	**0.747**	0.07	**0.268**	0.04	0.633	0.14
	SWT	0.697	**0.09**	0.231	**0.06**	**0.702**	**0.25**

Reconstruction is solely based on the decoded regimes. It allows for assessing the representativeness of the regimes: if the reconstructed signal is close to the original signal, then the regimes effectively capture the local dynamics of the environment and can be used for prediction. As long as consecutive observations follow the same regime, a unique linear model can predict them. Conversely, a regime change implies a break in the linear dynamics. It is therefore essential to leverage information about regime changes probabilities.

Let T be the transition matrix of the inferred Markov chain. The probability of leaving regime i between times t and $t+1$ follows a Bernoulli distribution with probability $p = 1 - T_{ii}$. Consequently, the number k of consecutive time steps without a regime change follows a geometric distribution with probability $\mathbb{P}(X = k) = (1-p)^{k-1}p$. This distribution can be used to estimate the horizon over which predictions can be made using the current regime linear model parameters.

III. PRELIMINARY RESULTS

This section reports on preliminary results to evaluate the effectiveness of our approach.

Compared configurations. We compare four experimental configurations: an AR model on raw traces (baseline), an AR model on SWT, an AR-HMM model on raw traces, and an AR-HMM model on SWT. The SWT is applied using Daubechies wavelets with three transformation levels to extract both fine and coarse information.

Harvesting traces. Configurations are evaluated on real energy harvesting traces collected in three piezoelectric environments: a jogger's movements, vibrations from an industrial washing machine, and vibrations from a moving car [7] [8]. The traces are filtered and normalized, and the model is trained on $1{,}000$ seconds of observations and evaluated on 50 seconds of unseen observations.

Metrics. *Reconstructibility* is evaluated with the coefficient of determination $R^2 = 1 - \frac{\sum_{t=1}^{n}(x_t - \hat{x}_t)^2}{\sum_{t=1}^{n}(x_t - \bar{x}_t)}$ where x_t is the actual harvested power at time t and $\hat{x}_t$ is the reconstructed power. An R^2 of 1 indicates complete explanatory power, whereas $R^2 \leq 0$ indicates none. *Persistence* is evaluated by calculating the average duration P (in seconds) of consecutive observations in the same regime.

Results. Figure 2 shows a trace example from the Car dataset, decoded and reconstructed with an AR-HMM on SWT. The reconstructed signal closely follows the original, illustrating the ability of our approach to represent the energy environment using linear models. Although brief regime changes suggest possible improvements in the choice of the representation space, some linear dynamics last several seconds, enabling reliable local predictions. Experimental results are presented in Table I. We observe that the AR model without HMM consistently fails to capture the power's non-linearities, supporting the need for signal decomposition into regimes. The AR-HMM on raw traces often achieves the highest R^2 score but tends to produce frequent regime changes. The AR-HMM on SWT offers the best tradeoff: it provides good reconstruction capabilities while generating fewer regime changes.

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