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Household Energy Demand Predictions for IoT Systems

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***Abstract*—In modern societies, the ubiquity of computing devices highlights how data processing capabilities transitioned from revolutionary novelty to commodity. Lowering prices of smartphones, intelligent doorbells, or internet-enabled lightbulbs drive the creation of large software platforms responsible for the intensive computations requiring resources that would overwhelm more modest devices. Nonetheless, some use cases cannot cope with delays introduced by this type of distributed computation. For example, demand response proposals for smart electrical grids can expect millisecond-level thresholds. One possible way of mitigating this issue is by adding decision-making to the device itself. It is a case of edge computing that keeps a frequent communication channel with a large, distributed control plane always open. However, having a concise, deterministic algorithm that can handle cases like consumption forecasting seems beyond our current understanding of electrical engineering. This restriction points to the need for some form of pattern matching process constantly updated by a training feedback loop. The edge device would handle decisions by applying this model trained by the central platform. This document investigates the options available for proposals for time-series forecasting, including modern machine learning techniques. It investigated the feasibility and trade-offs expected to satisfy the technical challenges posed by this scenario.**

***Index Terms*—Machine Learning, Internet of Things, Edge Computing**

# I. INTRODUCTION

The importance of demand-side control of consumer-grade electrical systems has increased in popularity in the past decade. It is now discussed as an integral component of research areas such as Smart Electrical Grids and Distributed energy generation. The underlying motivation for bringing this topic to a more central position is the overdue modernization of electrical distribution systems worldwide. There is a departure from a centralized, unidirectional control system toward more fine-grained distributed models.

Some technological breakthroughs did not fit the legacy top-down communication model. For example, the introduction of Solar and Wind generation requires a much more agile response given the unpredictable nature of their availability. The operator started dealing with greater levels of variance that more slow-moving forecasting models could not reliably manage.

This landscape gave rise to energy aggregation services acting as coordinators independent coordinators. Industry players place bids on supply requirements advertised by system operators. It is the first step in decentralizing control. However, decentralizing the generation control still requires more fine-grained information dissemination.

This level of transparency enables proposals from the demand-side of the energy distribution equation. Research is often not tied to the same constraints imposed by routine business concerns. There are countless proposals for more radical communication architectures inspired by many disciplines, from Neighbourhood-level microgrids to multi-layered energy distribution cells, similar to cellular telephone zoning.

This restructuring shares the traits of similar past modernization endeavours. One often overlooked is moving consumers from passive receivers of information to active participants on updated digital platforms. These platforms moved from simple broadcasting to a much more immersive bidirectional channel. The advertisement industry was the first to exploit how to establish feedback loops to drive revenue increase.

There is no reason why Smart electrical systems could not follow this example. Updates in the distribution network require moving to the same digital planforms used by digital advertisement players. Therefore, there is little reason to reinvent consumer data extraction tools. Most importantly, this strategy enables leveraging tried and tested methods for handling privacy and cybersecurity.

This document explores the beginning of this journey. It aims to understand the best strategy for understanding consumer behaviour and its relationship to the energy distribution system. The focus is on developing a reliable tool for forecasting household demand as the first step toward fleshing out a fully digital, bidirectional communication medium.

It starts by disambiguating the acronyms involved in developing such systems. It must interact with newer iterations of older concepts, like Fog Computing. Moreover, it must also provide some guidance on terminology that seems well defined but still suffer from conflicting details. J. Kampars, et al., 2021, provide a comprehensive survey of the technological landscape. It explores the multiple overlapping concepts between the Internet of Things (IoT), Edge Computing, and Cloud Platforms.

Another relevant survey is B. Sudharsan et al., 2021. The authors present several options for energy demand forecasting on embedded platforms. While this document cannot reach the same level of depth, it is essential to understand the practical implications of connecting and distributing forecasting models across distributed networks.

Finally, A. T. Eseye and M. Lehtonen, 2020, discuss the standard machine learning techniques employed for this project. The document performs a comprehensive analysis of Artificial Neural Networks in roughly the same terms stated by this research's objectives. It also provides parallels with competing implementations using Support Vector Machines.

# I. Methodology

Multiple academic disciplines are involved in proposing a solid implementation for an ambitious Smart Grid system. A fully fleshed-out plan requires much more than examining candidate machine learning implementations. However, this study cannot spare the resources necessary to perform due diligence in all required aspects. Therefore, the focus will remain on the study of the decision-making process.

This focus on software implementation implies a primarily quantitative exploration of resource consumption. Since there is no candidate hardware platform, there are no expected limits. The scenario comes with extra tasks such as defining credible baselines so the researcher can reach some form of conclusion.

Nonetheless, some theoretical guidelines can form a comfortable guardrail. We are discussing a time-series forecasting problem that fits a well-established statistical mould. There are clear baselines for how effective a model can perform. Most importantly, this framework allows experiments to quantify each proposal's effectiveness level.

The intersection between computer science and statistical model evaluation defines the point where automated decision-making becomes a viable option. For example, inspecting the behaviour of a dataset will allow us to compute the error margins of doing nothing. Assuming that previous readings are close enough to the subsequent measurement, there is little reason to waste computing cycles.

With this baseline, we can look for algorithms to improve this score. This step lets us put computational costs in context and define a price-per-point accuracy boost. This evaluation can rely on well-established time and space complexity analysis. There is no point in discussing strategies for proper assignment of responsibilities of components in the distributed architecture of a Smart Grid system if we do not know the costs involved in each stage.

Space complexity will inform the memory capacity required to build adaptative models and evaluate decisions. The size of these artefacts also impacts the required network bandwidth to operationalise an appropriate response time. Finally, it will inform the storage requirements of the platform. Keeping a database of consumer profiles may allow more sophisticated inferences, but it can also be prohibitively expensive.

Time complexity will dictate the level of responsiveness of the system. We already discussed moving from a slow-moving, centralised forecasting plan to a distributed, fine-grained and responsive one. Generating and updating models can be a bottleneck that restricts response times. But also, forecasting times can hamper the agility of the solution.

# II. Candidate Models

Household consumption injects a fair amount of unpredictability in the problem statement given its human component. There are some aspects that can be reasoned at a coarse-grained level. For example, daily seasonal patterns are undeniable (Figure 1). This type of information drives decision-processes in several disciplines having direct impact on the design of well-established supply chains. In the energy distribution space, these seasonal patterns are important drivers of supply-side planning.

This proposal explores a different pathway, more in line with the online connectivity patterns proposed by the modern Smart Electrical grid. The argument is that traditional seasonal windows do not capture single household demand behaviour with enough resolution to empower residents to drive energy conservation decisions. They are better suited to a centrally managed system, like the ones in place in the current control plane. The main idea of this article is not scraping the current model but refine it to include a more decentralised component where consumers interact directly through their daily routines.

Unfortunately, capturing consumption patterns in this resolution is not a trivial matter. Human behaviour has a notoriously chaotic component that challenges conventional modelling. For this reason, the research explores non-mainstream applications. It borrows from modern digital marketing platforms and their successful applications of non-linear model such as Artificial Neural Networks (ANN).

Before discussing possibilities, it is important to place some guidelines that constrain available options. ANNs are a popular academic field with a prolific community. The number of possible architectures increase every year. Nonetheless, the proposed solution cannot reasonably expend the same resources as state-of-the-art Transformer solutions employed in large language models. In fact, it goes in the opposite direction, favouring light-weight structures transmitted over the network.

However, the other side of the spectrum does not provide a straightforward option either. While Feed Forward Neural Networks (FFNN) can be easily embedded in simple devices, they might not provide adequate structural support. The problem lies in treating an extrapolation problem, that is, one that might not have a datapoint available to map its construction, as an interpolation problem.

Energy consumption models require a forecasting structure closer to a time series analysis. Patterns of neigbouring measurements inform the behaviour of future ones. FFNNs treat all datapoints in the same fashion. It does not provide a framework that can adaptatively map these sequential structures. The research will focus on a few candidates that exist between these boundaries. They must be simple enough to fit an embedded system but capture enough complexity to provide reliable forecasts.

## A. Convolutional Neural Networks

## B. Gated Recurrent Units

## C. Long-Term Short-Term Memory

# III. Implementation

# IV. Discussion

# V. Conclusion

References

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