ELEXIA

4th Press Release

Development of the flexibility functions and the digital twin

With an increasing proportion of renewable energy resources in the power grid, demand side energy management plays an increasingly important role in energy systems. The intermittency of renewables and the replacement of non-renewable resources (gas, oil, coal) makes the operation of such systems more challenging. A key solution is flexibility, where the energy end users are encouraged to consume electricity when the renewable energy generation is high and reduce it when it is low. This is commonly implemented with dynamic pricing schemes that reflect the available energy in the grid. The end users are then encouraged to consume electricity when it is cheap to reduce their costs. For maximal efficiency, this requires a wide deployment of price-sensitive controllers that react to these price signals in real-time.

There remains a series of major challenges for making such systems efficient. An important open question is quantifying the amount of flexible energy within an energy system. Flexibility is traditionally quantified by metrics such as activation time, peak demand reduction, shiftable load or cost savings. While such metrics were developed for power grid applications, their application to e.g. buildings is more complex, as it their demand profiles are influenced by a wide variety of factors. As buildings are not as widely monitored by sensors and depend on difficult to predict human activity, it makes the prediction of building electricity demand quite challenging. Furthermore, the application of previous quantification methodologies requires knowledge of the available equipment, their operational characteristics and information about the underlying control algorithms. This makes this type of characterisation of flexibility unscalable.

Recent developments aim to combine the operational requirements of maintaining operational objectives (e.g. maintaining temperature in a building) together with the economic aspects, that is minimising electricity costs. The main idea is to apply a dynamic time series model, often used in economics, to model the energy demand of an energy system in function of price. It can be used for example to measure the impact of specific pricing schemes on demand. This would allow to model flexibility as the responsiveness of energy demand to changes in price. Therefore, the idea is to model flexibility dynamically with a “flexibility function”, which is a function from prices to demands. This function can be estimated from existing demand profiles, using various machine learning techniques.

Within the ELEXIA project, we aim to extend flexibility functions to models that not only take prices as inputs, but possibly also other variables, such as temperature or time of the day. This makes the methodology more applicable to systems where price is not the only driving factor, such as buildings. As in previous work, we model demand via a state-space model, but generalise it to model of the form:

$$\begin{aligned} \boldsymbol{dZ}_t &= \mu(\boldsymbol{Z}_t)\boldsymbol{du}_t + \sigma(\boldsymbol{Z}_t)\boldsymbol{dW}_t, \\ \boldsymbol{O}_t &= \boldsymbol{F}(\boldsymbol{Z}_t) + \varepsilon_t, \end{aligned}$$

In this equation, we have:

- A latent state $\boldsymbol{Z}_t$, which can be thought (if modelled accordingly) as a state of charge. For example, if it is close to 0, then the system is inflexible, while if it is close to 1 it is flexible. It can also be multidimensional for more complex systems.

- Observations $\boldsymbol{O}_t$, which include at least the energy demand Y_t of the system. However, we can optionally also include other endogenous variables that may be considered by the controller. For example, if indoor temperature is monitored, it would provide valuable additional information to assess whether the system is flexible or not.
- Exogenous inputs $\boldsymbol{u}_t$, which include at least energy prices p_t. However, we should further add other exogenous explanatory variables, such as time of the day t or outdoor temperature, which may be particularly relevant to infer the behaviour of the price-sensitive controller and the resulting demand profiles.
- A multivariate Brownian motion $\boldsymbol{W}_t$, which models the effect of other unknown variables on flexibility that are due to other factors than the ones captured by such as human activity or simply corresponds to our lack of information about the system.
- Dynamic functions $\mu(\boldsymbol{Z}_t), \sigma(\boldsymbol{Z}_t)$ and $\boldsymbol{F}(\boldsymbol{Z}_t)$, which can be fixed parameters, predetermined functions or models learned from the data. We can for example use a grey-box model, a generalised linear model or a neural network to model these functions and estimate their parameters by maximising likelihood.

This type of functions has a wide number of applications within energy systems. For example, we could use the function to derive commonly used flexibility characterisations (peak demand reduction, flexible load, cost savings). Furthermore, it could be used for system identification of model-based controllers, designing orders in flexibility markets, improving coordination between TSOs and DSOs. Future work may also be used to use it as a tool for designing dynamic pricing schemes that can provide indirect peak shaving in an energy system. Another application that will be investigated within the **ELEXIA** project is to estimate the amount of flexible energy in energy system planning. Accurately estimating and leveraging the available flexibilities may lead to reduced investment costs.

ABOUT THE PROJECT

ELEXIA (Demonstration of a digitized energy system integration across sectors enhancing flexibility and resilience towards efficient, sustainable, cost-optimised, affordable, secure, and stable energy supply) is anchored under the EU Green Deal & the EU Strategy for Energy System Integration. It is in line with the Paris Agreement and the UN's 2030 Agenda for Sustainable Development.

ELEXIA contributes to establishing concrete pathways to achieve fossil fuel independence by harnessing the energy system's latent flexibility through integration across sectors, data intelligence, and planning towards 2050 European goals.

CONSORTIUM

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