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EXTENDED ABSTRACT

Title: Cooperation mechanisms within energy storage systems optimisation models

Authors and e-mail of all:
Emilio L. Cano[1] (emilio.lcano@uclm.es)
Javier M. Moguerza[2] (javier.moguerza@urjc.es)

Department:
[1]Quantitative Methods and Socio-economic Development, Institute for Regional Development (IDR)
[2]Computer Science and Statistics

University:
[1] University of Castilla-La Mancha
[2] Rey Juan Carlos University

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Abstract:

Cooperation Mechanisms were created by the European Commission (EC) in the Renewable Energy Directive 2009/28/EC to facilitate cross-border support of renewable energy, in the framework of the promotion of the use of energy from renewable sources. Thus, Member States (MS) are able to explore potentials and achieve efficiency improvements regarding their 2020 renewable energy sources (RES) targets. Through cooperation mechanisms, MS can agree on transnational support of RES and take advantage of more cost-efficient potentials. In articles 6 to 11 of the Directive, three different types of mechanisms convey such cooperation, namely: statistical transfer, joint projects between MS, and Joint projects with third countries. Even though energy storage is not a proper RES, it is playing an increasingly key-enabling role for tackling some of the RES challenges, e.g., intermittence. In fact, a considerable amount of research is being carried out to develop systems and models for energy storage efficiency and management, at both large scale and small scale.

In this work, we explore how cooperation mechanisms can be integrated within optimization models typically used at local scales. Joint projects between neighbor countries with physical transfer of energy are clearly successful candidates for this aim. Moreover, statistical transfer is investigated as a compensation for RES targets, but also as a carrier to provide insights for policy making that improve global sustainability from regional decisions.

An optimization model has been developed to model energy storage systems (ESS) that allows for considering not only existing technologies, but also emerging or foreseen technologies. The Combined ESS model allows for energy transfer between energy silos, allowing different energy types and technologies. The model provides insights for policy makers and market stakeholders on which technologies have more potential in order to prioritize funding and/or investments. The model is an evolution of previously developed models focused on energy efficiency at the building level. In [1], an optimization model for decision making on energy technologies was developed. That deterministic model was extended to a stochastic approach in [2] and implemented in a Decision Support System in [3].

The optimization model developed under a Mathematical Programming framework is eventually a Linear Programming (LP) problem, in which a cost function is to be optimized, i.e., minimized. This function cost adds up investment costs, Operation & Maintenance (OM) costs, transmission costs, and energy market costs, i.e., energy bought and sold. Subsidies are also considered, and eventually could turn into decision variables in order to provide policy advice. The objective is subject to several types of constraints. First, energy balance, as the system is supposed to provide energy to a set of energy uses. Those uses can be fed by energy storage technologies, which are the main subject of study, but also directly by energy grids. Moreover, one use could be the selling of energy to the market, becoming a negative term in the objective function to be minimized. The system capacity is managed by a set of equations and bounds to keep the energy flows within the available technologies. A computation of the energy storage inventory is needed throughout the time span, which is managed by another set of equations with between-periods links. For all these equations, appropriate parameters and variables are defined over their applicable indices of the following sets:

T: Time period
I: Storage technology
J: Energy type
K: Energy source
L: Energy use

Thus, the system energy flow corresponding to the model sets is shown in Figure 1. Energy can be interchanged among storage technologies (I) and eventually released to a given use (L); Energy sources (K) feed storage technologies (I), but also can be directly used as use (L). All these flows may imply conversion between one type of energy (K) and another, e.g., solar to electricity and so on; finally, the model is multi-period, throughout several points in time (T).

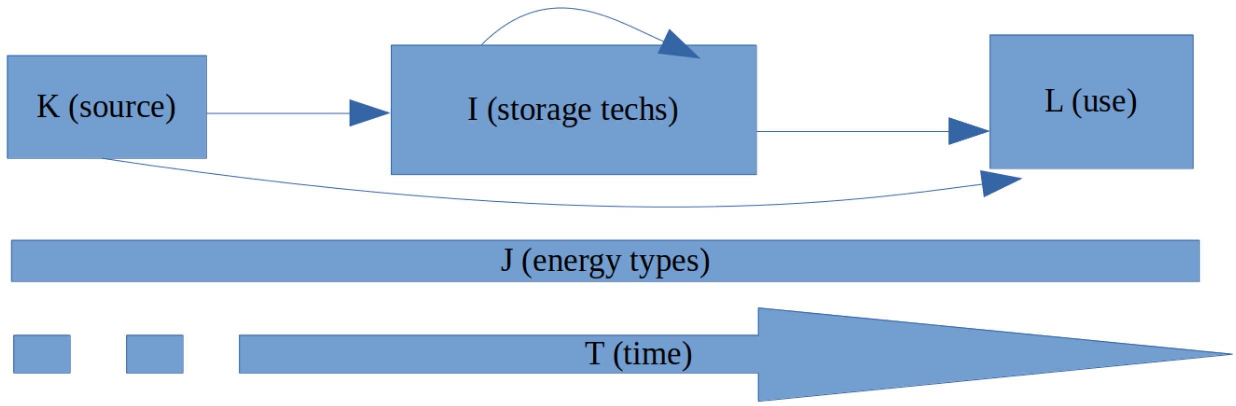

Figure 1: Energy flows

In addition to the cost parameters in the objective function, efficiency and boundary parameters are defined, as well as the energy use requirements. With regard to the decision variables, the most relevant ones are those related with the capacity to be installed of each energy storage technology, at any time. In addition, instrumental variables model operation decisions throughout time until the decision horizon. Such variables include, e.g., the energy to be purchased, stored, or delivered to be used for each period.

The general-purpose model described above, is intended to be used at several scopes, from small-scale applications, e.g., Internet of Things (IoT), weareables, etc., to large-scale applications, e.g., buildings, neighborhoods, or grids. Going further, the model is suitable to be used at a regional level, and therefore within the scope of the cooperation mechanisms outlined at the beginning of this article.

In order to illustrate the usefulness of the model at that scope, an illustrative example for a plausible scenario has been tested. In this example, we consider three hypothetical neighbor countries, say, Country x, Country y, and Country z, with connected electrical grids that supply border cities. The cities in each country have different populations, household and industrial equipment, and, therefore, different use needs. Such demand is fulfilled with each one own grid. In addition to the grid, each country has diverse resources, namely: country x has a wind farm, country y has a photovoltaic (PV) power station, and country z has a Natural Gas (NG) fueled combined-cycle power plant. Figure 2 shows graphically this situation.

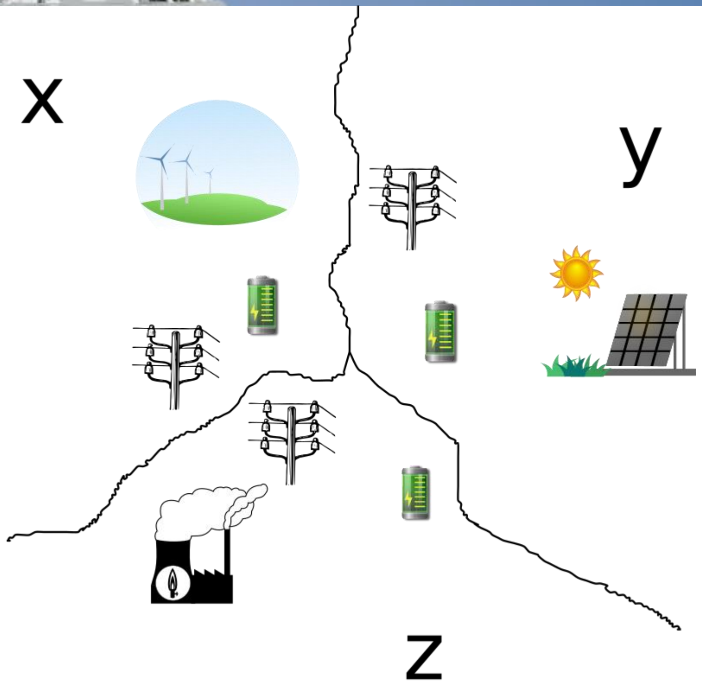

Figure 2: Illustrative example diagram

The decision problem could be the installation of large-scale batteries near the borders in any of the three countries in order to assess cooperation mechanisms defined as "Joint projects between neighbor countries with physical transfer of energy". Parameter values are set from the literature to model the energy flows from resources to storage and use as shown in Figure 1. For cost parameters, we use data from the Lazard's Levelized Cost of Storage (LCOS) analysis [4]. With this setup, the number of variables is 14400, and the number of constraints is 1800. The problem data has been generated and arranged for the problem to be solved using the R statistical software and programming language [5] ROI package [6] [7] and the GLPK solver [8] [9].

Preliminary results show that the solution for the model instance provides reasonable decisions for this setup. To achieve that, some decision variables values needed to be fixed in the instance. For example, investments were only allowed at some time points, and therefore for the rest of the periods the variable for new capacity to be installed were fixed to zero. Thus, this illustrative example paves the way for more complex instances and extensions of the model. For example, other large-scale storage technologies such as pumped hydro-storage, flywheel energy storage, or compressed air energy storage.

We outline now some of the foreseen improvements and further work that we are investigating. With regard to the model, some technologies might require a discrete scale for the deployment. For example, for PV panels we can stick on continuous decisions because the difference in capacity adding one PV panel is small, but, for example, for CHP technologies, that difference could be large. Hence, the problem should become a Mixed Integer Linear Programming (MILP) one. The model will evolve in order to include more relevant socio-economic and environmental features, by means of new constraints that include emissions limits or efficiency requirements. Moreover, the objective function could also account for emissions trading or efficiency penalties. Another important model setting to be run, is fixing the decisions on

investments, as a desirable result of a policy, e.g., to invest in PV panels, and turn the subsidies parameters into variables, probably with some modifications of the constraints and objective. Thus, policy makers could use the output of those types of instances in order to align future regulations.

Regarding statistical transfer, further investigation is needed in order to learn how to include the virtual exchange within this model designed for physical transfer. This will likely need to include new constraints, variables, cost parameters, and terms in the objective function (or define a multi-objective one).

Finally, uncertainty and risks will be taken into account by means of Stochastic Programming and risk management measures in order to be included in a forthcoming stochastic version of the model.

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