Gaspard Monge Program for Optimization, operational research and their interactions with Data Sciences

2023 Call for projects

IROE appendix

SUMMARY

1 Introduction

This document aims at describing in detail some of the problems encountered within the field of energy management. This document also gives an idea of the work already completed or in progress on these topics, and the main difficulties already encountered. The listed research directions are given as an example. The submitted projects may address other issues than those listed below, consider methods of resolution that are completely different or that are a continuation of the work referenced.

Proposers are strongly encouraged to contact the experts at EDF Lab on each subject in order to have a thorough knowledge of the issues and research work already completed or planned for on each topic. To this end, please contact the PGMO board (mailto: pgmo@fondation-hadamard.fr).

2 Background: the main issues in Energy Management

2.1 Managing the Supply-Demand balance

In order to generate electricity, a diverse portfolio of physical and financial assets (supply) is available in order to meet the customers' consumption (demand). The balance between supply and demand must be achieved within each time period in order to avoid the risk of physical system failures. The objective of generation management is to achieve this balance at minimal cost.

2.1.1 Uncertainties

Many uncertainties significantly impact the management of production, from both the system safety and economic points of view. These uncertainties are mainly due to climate (temperature -which strongly influences the demand for electricity, hydraulic inflows, wind, cloud cover, sun), outages of power plants, prices on the energy markets and renewable production (wind and photovoltaic). These uncertainty factors are strongly correlated to each other.

2.1.2 A diversified generation and flexibility assets portfolio

The physical offer comprises all generation and flexibility assets, including load management. It includes both traditional centralised assets and distributed assets. Centralised here means that the assets are connected to the transmission network. Centralised assets are generating units (power plants incl. renewables, hydro valleys), demand management, multi-energy assets and storage. Distributed assets are connected to the distribution network. Distributed assets are generating units incl. renewables, load management, electric mobility, storage and multi-energy assets. Distributed assets may be aggregates of elementary assets with diverse representations of aggregation (aggregators).

- **Thermal assets**, consisting of nuclear and conventional thermal power plants: coal, oil, gas turbines, combined cycle gas turbines (CCGT). Each plant has to account for a set of operational constraints (production ranges, minimum outage or operational periods, start-up curves, possible shared fuel stocks with other plants, etc.) and is characterized by a possibly complex cost structure (fixed costs or variable with respect to the amount of fuel, start-up costs, etc.), specific contributions to ancillary services, emissions, etc.
- **Hydraulic assets**, consisting of hydraulic plants (including pumped storage) are located in hydro valleys with water pathways between the various assets. Typically the assets are organised in a cascading structure and various reservoirs allow for (partial) storage of water. The water pathways can have a different flow duration depending on where the plants are located. Moreover, constraints on reservoirs (minimum and maximum volumes, water value, etc.), plants (power limitations, discrete operating points, gradient constraints, change of direction constraints, flow delays, water head effects, etc.) and most importantly a representation of the "hydro-production function" all have to be accounted for.
- **Intermittent renewable generation :** e.g. wind, solar
- **Electricity load**, including nonflexible demand and flexible demand (e.g. load shifting) both centralized and distributed;
- **Distributed and centralised storage**;

- **Aggregators** i.e., actors that provide aggregation services through the management of a set of distributed assets (generation, storage, demand response through contracts with some flexible customers, etc.);
- **Multi-energy assets** providing flexibilities to the electricity system (power-to-gas, power-to-heat…). However in order to assess the availability of multi-energy carriers, it may be necessary to represent with some detail constraints related to the these other energy carriers (gas, heat).

2.1.3 Markets

- Electricity and commodities spot markets
- Future markets
- Capacity markets
- Intra-day markets

2.1.4 Environmental constraints

The directives and guidelines initiated by the European Union in order to foster a general approach against climate change and for environmental protection have a strong impact on the management of the supply-demand balance for energy producers:

- control of greenhouse gas emissions: management of pollutant emissions;
- taking the increase of the renewable generation (wind, photovoltaic ...) into account, inducing high uncertainties and a need for flexibility.

2.2 The challenge : manage a diversified portfolio that's very large in size

The goal is to manage the portfolio (generation assets and contracts) with the objective of minimizing costs while considering uncertainties. This problem is not solvable in the present state of knowledge, because of its very large size and mathematical complexity. Thus, it has to be decomposed into a set of different problems per time frame. Different considerations are taken into account at different time frames. At distant time horizons, the most important uncertainty factors (weather, uncertainty on the operation of power plants, market risks ...) are represented very accurately (in practice as a random process or a very large number of scenarios), while the power generation assets are described only approximately. By the same token, at close time horizons, generation assets are described very precisely but uncertainties are not necessarily represented. Each time horizon provides a set of indicators for the time horizons that are closer to real-time, this is in order to keep the real time operation consistent with our vision of the future.

Despite decomposing the problem into different sub-problems at different time frames, the optimization problems within each time frame remain very large. The challenge remains to obtain accurate solutions within reasonable computing times to allow for effective production planning. It may thus well be that it is more appropriate to inherently link the various time horizons together. This, so that the need for flexibility arising as a result of constrained operation in real time, can be properly appreciated at the various larger time scales.

2.2.1 Long-Term

In the long term (five to twenty years), the challenges are:

- **Simulating the evolution of fuel and electricity prices**, which are based on the calculation of underlying fundamentals, i.e., a model of the supply-demand balance over a set of interconnected geographical areas;
- **Planning investments in new generation assets**. Investment planning methods are based on a minimization of the supply-demand balance cost, the result being the optimal (and robust to uncertainties such as physical hazards, economic and regulatory uncertainties) distribution of technologies to meet base and peak demand.

More details may be found in [LAB2011].

2.2.2 Medium-Term

In the medium-term (one to five years), the challenges are:

- **Defining the optimal outage schedule for the refuelling and maintenance of nuclear reactors**: the objective is to minimize generation and refuelling costs while satisfying demand and reactor operation constraints (operational and outage constraints), all in the presence of various uncertainties. A detailed description can be found on the PGMO web site and in [ROAD2010].
- **Defining coordinated management strategies for a set of stocks** (lakes, fuel stocks, stocks of (load) shedding, pollutant emission stocks): the aim is to calculate optimal strategies that adapt themselves to uncertainty (feedback, "multi-stage" with scheduling modifications). One of the main issues is related to the joint optimization of all stocks. The techniques currently used (dynamic programming) become difficult to solve when more than three different stocks are considered. Approaches such as SDDP (e.g., [AOS2019]) have challenges of their own (e.g., underlying structural requirements). Moreover uncertainty has to be represented with a certain accuracy to obtain meaningful results (see [L2008], [G2010] for more details). These classic problems can thus not yet be said to have been solved in a satisfactory way.

2.2.3 Short-Term

In the short-term (a few days to a few hours), the challenge is to define a day-ahead production plan and to adjust to near real-time schedules to meet the actual demand. The main issues are:

- **Calculating minimum cost generation schedules for the next day**, including all constraints on generation assets, meeting the demand constraint (power and various types of spinning reserves) while providing recourse schedules in order to take into account future uncertainties;
- **Optimizing intra-day rescheduling** ("redéclarations" in French): at each hour of the day, the producer must change the schedules of a limited number of assets (thermal assets or parts of hydro-valleys) in order to reduce the real-time difference between production and consumption due to uncertainties on demand and availability of assets;
- **Calculating generation margins and optimizing reserves**;
- **Calculating balancing offers** for the adjustment market.

More details are available in [ADLFLT2018]. Further detailed descriptions of the problem, as well as presentations explaining the state of the art on this issue are available on the PGMO website.

3 IROE Main research topics

The list of all already funded PGMO projects may be found on the PGMO website.

3.1 Energy Management

3.1.1 Long-term and investments

Models based on the underlying physics of the system are designed to calculate the long-term prices of energy on a set of interconnected areas. In the case of electricity, the main difficulties come from the representation of strategies for the management of many stocks/inventories with various – and different - seasonalities (water storage in particular), the intermittence of renewable energy production, the representation of the transmission network and the amount of flexibility made possible by demand response. Another difficulty is to anticipate the impact of the competition between primary energies on the long term electricity demand. The mathematical model dealing with these issues is a problem of economic stability across Europe, each area aiming at minimizing its costs while providing energy to its customers and contributing to the global European equilibrium. Balance prices calculated with such a model can be interpreted as price indicators of electric energy.

The issue of Investment decision problems is to determine the technologies in which it will be best to invest in the future in order to meet energy demand. Due to the nature of those investments (building power plants or storage capacity, network expansion etc.) it is necessary to anticipate them far in advance. In other words it is necessary to take all relevant information into account to determine the right sizing of production facilities for a horizon of 15-20 years in the future.

3.1.2 Energy management in decentralized systems

The energy systems in Europe have originally been designed in order to reach the best possible economical objective in each country for satisfying a given demand. Economy of scale principles were applied and lead to the construction of a generation mix mainly composed of large generation assets. Moreover, a centralised generating mix was seen to be the best solution to serve demand. This is because centralisation allows for the aggregation of multiple highly uncertain and variable demands thus reaching a relatively stable global demand.

The emergence of a high share of intermittent renewable energy sources in the energy system leads to many difficulties, due to their characteristics (intermittent, hardly predictable, usually non flexible, usually not contributing to frequency stability services, spread all over the country/continent - not always close to demand, connected to the distribution network thus constrained by its size).

Besides, recent and forthcoming regulatory and technical evolutions are deeply transforming the system with the upcoming local demand management tools and a more proactive stance of actors in the field, including customers.

Therefore, the energy management tools need to change significantly while contributions to flexibility will gain "significant" value which will make their precise valuation essential.

Managing such decentralized energy systems covers many interesting problems depending on which viewpoint we will pick up:

- The regulator is interested in designing rules of interaction between the different actors in order to achieve global efficiency of the system;
- The Distribution System Operator (DSO) is interested in alleviating distribution grid constraints (e.g. voltage stability), using all available local flexibilities including modification of grid topology, energy storage, curtailment, consumption flexibilities, . . . In the long-term perspective the DSO is interested in designing efficient connecting rules, incentives, tariffs;
- The Transmission System Operator (TSO) is interested in alleviating transmission grid constraints (e.g. congestion) and ensuring the real time balance of the system using flexibilities to provide (ancillary) services; Some of these flexibilities could result from prosumers offering various degrees of flexibility in the management of their consumption.
- Producers/Providers are interested in managing a mixed portfolio including (controllable and variable) generation, storage, (flexible and non-flexible) consumption taking into account uncertainties at multiple time scales (including short-term operation decisions as well as mid-term and long-term decisions such as investment decisions or tariff and contract design); The impact of uncertainty and notably the amount

of variability that needs to be accounted for can also depend on the considered time scale – and is moreover relevant to estimate, in an appropriate way, the amount of required flexibility.
- Aggregators are aiming at controlling an aggregate of distributed flexibilities, while preserving both privacy and conflicting objectives of flexible agents (consumers or prosumers);
- Prosumers and consumers are willing to optimize their local objectives (e.g. maximizing self-consumption, minimizing their bill) while taking into account local uncertainties at multiple geographical scales: house, district,

In all these items, contributions of multi-energy assets should be integrated.

This topic is fairly new and deals with issues at different levels of the supply-demand balance process.

Some mathematical approaches were identified including:

- Decomposition Methods
- Distributed optimization
- Bilevel Optimisation
- Game Theory
- Mecanism design
- Mean-field control and game
- Learning and online optimization

3.1.3 Grid stability in a system with a high share of renewable energy sources

The growing share of variable renewable energy sources VRES (such as windpower or photovoltaic) raises major challenges for the electricity systems:

- The spatial repartition of the variable renewable generation does not always coincide with areas of high demand (e.g. urban centers) and, as a consequence, can lead to transportation of the electricity over long distances. Such power flows may create congestion issues at distribution and transmission levels.
- In an AC network, any imbalance between supply and demand results in a deviation of frequency. On-line synchronous spinning machines (i.e. nuclear, hydro, coal, etc.) currently ensure the stability of the grid by providing inertia (linked to the amount of kinetic energy stored in the rotating masses of spinning machines) and frequency regulation. The substitution of the conventional generation by VRES may decrease the capacity to maintain the frequency at a satisfactory level.
- As energy losses and supply quality depend on the voltage value, voltage control is essential for reliable and cost-effective transmission of electricity. Traditionally, specific regulators and provision of reactive power by the conventional generators ensure the voltage control respectively at distribution and transmission level. Voltage levels must remain within predefined bounds, but as a result of intermittency and variability, high spikes may occur.

The main challenge is then to improve grid dynamics considerations such as frequency regulation and voltage control within all energy management optimization models.

3.1.4 Scheduling of nuclear outage maintenance and refueling

Optimizing nuclear unit outages is of significant economic importance for EDF, as these outages induce substitute production by other more expensive means to fulfil electricity demand. Furthermore, due to the main part of nuclear production in EDF’s production-mix, nuclear outage planning plays a key role in the whole energy management chain. More precisely the objective of the problem is to determine the outage dates, the quantities of fuel to refill and production planning for all plants. The outage dates must satisfy resource constraints shared by outages and lead to a feasible production plan for each nuclear units. To be feasible, a production plan must satisfy maximum fuel level constraints before and after reload as well as some specific constraints on production levels during the production phases. Finally, given that this optimization is done on a multi-year planning horizon and re-optimized every month with potential updates or additional constraints, most of the data is not known at the time of optimization. This problem has several challenging aspects: the specific operating constraints of nuclear units, the large scale and the multi-step characteristics of the problem and the stochasticity of both the demand and non-nuclear unit availability. A further aspect that could be noted is the necessary stability of the resulting optimal solution w.r.t. perturbations.

This very large stochastic combinatorial optimization problem was proposed as the topic of the EURO/ROADEF challenge in 2010 [ROAD2010], in a simplified form. In particular, neither the uncertainties on the availability of nuclear production units nor the "multi-stage" aspect of the operational process, were taken into account. The solutions offered by the top teams, mostly based on "Local Search" approaches, can provide good solutions quite quickly, but cannot guarantee optimality and do not take any robustness criteria into account. That is why some work was initiated, aiming to investigate exact resolution methods, capable of taking into account the missing aspects of the EURO/ROADEF Challenge.

These works can be classified into two broad categories:

- Prospective research on the potential contributions of Semi-Defined Positive programming, including robust formulations or based on probability constraints to take uncertainties into account (e.g., [G2013]).
- More applied research, aiming at using Dantzig-Wolfe like decomposition techniques (column generation) and Benders like methods (cuts generation) on "extended" reformulations of the complete problem, taking the uncertainties on the duration of the outages into account and the problem of the stability of the outage schedules calculated in the multi-step decision process. (See [WRCAL 2013], [PWEJPBP 2014], [GRI2018]). This second category of methods, based on reformulation and "cut and price" techniques, has revealed itself very fruitful and led to valuable results on the real operational problem by solving to optimality the deterministic problem and computing good quality solutions on stochastic models where several stochastic scenarios are considered to model the stochasticity of the demand and non-nuclear units availabilities.

Nowadays, the evolution of the production park (closure of some nuclear units and growing part of renewable energy sources) combined with needs of robustness reinforced by the Covid crisis confirmed the need of taking into account uncertainties impacting nuclear units and ensuring the stability of the planning over time. Hence, research must be strengthened and carried on in this direction, especially on the two following topics:

- Robustness of the solution when facing random events, namely outages duration extents, nuclear units availabilities and wind/solar production depth;

- Stabilization of the solutions in the multi-stage resolution process, trying to take into account recourses on the forecasted outage dates calculated each month, provided by the future re-optimizations on the sliding horizon.

3.1.5 Short-term Generation Scheduling

The "unit commitment" problem consists of finding a minimum cost operating program for all power plants:

- providing adequate system services;
- ensuring the supply-demand balance at every time period (currently defined as every half-hour but could be also quarter of an hour or less);
- respecting all operational constraints.

Daily and Weekly Optimization

The objective is to determine the optimal generation schedule which minimizes costs (production costs and start-up costs), while meeting a set of constraints. Constraints include numerous operational constraints that affect thermal and hydraulic power plants and meeting exactly a set of "demands" (consumption, reserve capacity and system services). Solving this problem provides a reference schedule for the day to come.

This unit commitment problem is already well-known and researched. The current solution is a combination of Lagrangian dualization, price-decomposition and bundle algorithms (see [LS1994]). This gives a first schedule which will then be adapted using an Augmented Lagrangian technique combined with the use of the auxiliary problem principle to get the reference schedule (see [CZ1984], [BR1992], [MS1983], [DGL2005]). This solution gives excellent results on the historical deterministic problem.

Recently, the strong increase of "new" renewable energies (wind, solar) has forced us to rethink this problem. "Historical" uncertainties (consumption, water intake, failures) could be neglected on a very short-term horizon, it is no longer the case for these new uncertainty factors. This is due to their high non-predictability (we have no reliable forecasts beyond a few hours) and their intermittent nature (e.g. passing clouds can reduce the photovoltaic generation abruptly to 0). It is essential to address these phenomena.

- First, all operational constraints must be finely modelled in order to benefit from the flexibility of all production facilities, particularly in cascading reservoir management. This leads to the introduction of many non-convex or binary constraints. Detailed modelling of the constraints induces difficulties on the overall resolution of the problem because the sub-problems arising from the price decomposition become more difficult to solve, so are solved in an approximate way which is not compatible with the traditional algorithm. The recent family of bundle approaches allowing for inexact oracles provides a nifty way to include "inexactly" solved subproblems. This theory is very well studied. However moving to a new scale of problems (e.g., European UC) – ideally asynchronous methods need to be developed. These could be asynchronous bundle approaches or asynchronous versions of ADMM-like approaches. Both are challenging topics if (artificial) synchronisation is not included.
- Secondly, uncertainty must be taken into account through the calculation of robust production programs, i.e., where the cost of adapting to the occurrence of intra-day hazards is minimal. This problem can be formalized as a problem with recourse. Work has been done on a robust approach without recourse decisions, as well as a robust approaches with recourse decisions but on small convex problems (cf. [BS2011] [Ap2007] [AHMZ2011]). Recent advances include the consideration of full scale unit-commitment problems as recourse sub-problems (e.g., [ALM2017] and references therein). Extensions will need to account for the interaction with "local structures" – possible having their own management principles.

Intra-Day Optimization and Re-Scheduling

Regulatory developments have led to formulate a new problem on the intra-day horizon: recalculating production schedules by solving the same problem as above, taking into account data variation that have occurred since the daily schedule has been computed. Some aspects of the daily problem have been simplified at the intraday horizon: flow constraints in hydraulic valleys are replaced by min/max energy constraints on subsets of hydraulic units.

The intraday problem also features a so-called re-scheduling constraint: for each geographical zone, there is a maximum number of hydraulic plants for which the reference schedule can be changed. This constraint is both coupling and combinatorial. Heuristic methods have been considered: the problem is decomposed into a phase of selection of plants in which the schedule will be changed then a phase of optimization of the schedules of these plants.

The current intraday problem is frontally solved by a MILP solver. Therefore a particular attention is given to obtain an efficient formulation for the problem, as well as a good quality "MIP start" solution.

Recent regulatory evolutions may make it necessary to reduce the time steps of the models. Typical timestep in the daily/intraday process is 30 minutes which may go down to 15 or even 5 minutes. An answer to these changes may be to have a time continuous model, which may lead to developing completely different optimization methodologies. The approach currently under investigation remains with a discrete time model, and performs a price decomposition of the problem, coordinated by a bundle algorithm.

3.1.6 Optimization of cascading reservoir systems

In the long and medium-term, the objective is to calculate good management strategies for the hydro valleys, taking constraints on reservoir levels into account. In the short term, the problem amounts to computing feasible programs (i.e. satisfying the constraints) in order to allow the use of all flexibilities of the hydraulic park.

Long and medium term

The main difficulty is to calculate the management strategies for coordinated reservoirs while dealing with uncertainties. Some solutions to the classical problem where the reservoirs have to respect a coupling demand constraint already exist. For more complex structures, for instance 'cascade' e.g. when it comes to coordinating all the reservoirs of one hydraulic valley, effective methods are still being defined (see [E2008], [L2008], [B2004], [D2006], [CCD2009], [PDG2011], [VP2011], [RS2011]). The stochastic decomposition method developed in the context of the global supply-demand balance [G2010] has been extended to the case of cascading reservoirs by [A2013]. A formulation with probability constraints (for taking into account the volume probability constraints on reservoirs) was proposed in [A2013]; the resolution method is based on the dualisation of the probabilistic constraint.

Beyond these approaches – a novel question also involves the notion of value of water in of itself. Indeed traditionally mid-term management of water resources is partially performed in order to compute the value of water, which is handed down to shorter term optimization problems. The natural candidate for the value of water is the value of substitution – traditionally related to the cost of thermal assets. The value of water in itself depends naturally on time, the available amount of water currently, and uncertainty. It is typically communicated through a "cost-to-go" function or, in fact, its first-order information. Now in a system with a high share of renewable – fatal generation – the substitution cost structure naturally flattens out. It is an open research question what impact this has on either the definition of the value of water, the stability of the currently employed algorithms or the way in which the cost-to-go function can be transmitted to shorter term optimization problems.

Short-term

The main difficulty is to solve accurately, and in a very short calculation time, a large mixed integer problem, characterized by very strong constraints. The integer structure of the problem comes from a specific discretization of the hydro-production function. Moreover in short-term optimization, there is a need to account for the amount of spinning reserves generated by the various hydro assets. The dependency of the available amount of generation in terms of spinning reserves has an even more complicated dependency on the flow rate than the active power output. Efficiently solving cascading reservoir systems remains a challenge.

Another challenge would be to dispose of native MILP solvers for solving the hydro-valley optimization problem. Current works focus in particular on the implementation of a Branch&Bound algorithm dedicated to the hydro problem. Related research questions non-exhaustively include: design of tree exploration and branching rules, development of a good quality primal heuristic and implementation of an efficient linear relaxation of the problem.

3.2 Multi-energy systems

Multi-energy systems (MES) involve the cooperation of different types of networks in order to maximize the efficiency of the energy provided while minimizing the costs and satisfying the demand. Another prerequisite is to follow environmental constraints regulations to cope with the energy transition. The optimization of MES is at least a two-stage process:

- The design of an efficient network: selecting the best utilities, sizing the infrastructures (such as storage units), the topology being a cornerstone in running such networks. This phase also encompasses defining the system geographical limits and aims at minimizing the investments costs. MES may include electricity networks (and renewable production utilities), gas supply, heating and cooling district networks, mass networks (from industries for example), storage units and/or innovative ways of producing energy (hydrogen for instance).
- Operating the MES : finding the best production schedules while minimizing the operating costs under resource and technical constraints. The MES takes into account the economic dimension: each actor of the grid must find benefits when cooperating to make the process sustainable.

The following research topics could be of use for this subject:

- Finding an efficient design network when actors are already present on a given area.
- Selecting which actors must interact together and the scale of the interactions: the optimization problem might be decomposed into several MES areas.
- Re-optimizing the MES schedule when failures occur.
- Finding the best economic compromise for both the MES operator and the individual actors of the grid.

3.3 Efficient and electrical mobility

3.3.1 <u>Electric Vehicles</u>

The development of electric mobility leads to multiple research questions, which include:

- [(very) long-term investment decisions] electrical system investment decisions (e.g., the choice and design of power plants) could be dependent on the presence of a large-scale flexibility on Electric Vehicle (EV) charging. It could represent a significant storage mean, even if not always connected to the electricity system. The proper representation of a large "aggregate" EV in investment models is a key question in this direction;
- **[long-term "strategic" decisions]** Electric Vehicle (EV) charging infrastructure location and sizing - for standard individual / fleet mobility usage, or new mobility services (autonomous / shared mobility);
- **[mid-term decisions] charging contract or tariff definition, possibly including a participation to a flexibility system[1]. Such contracts must be designed such that: charging cost is affordable for EV users; EV users are incentivized to take part of the flexibility mechanisms (positive net benefit when participating); the "global" performance of EV charging is beneficial for the charging operator/"aggregator" (total charging cost is minimized in a site, or flexibility benefits maximized);**
- **[short-term "operational" decisions]** "Smart charging" (i.e. EV consumption profile(s) scheduling) of one or multiple EVs (at home, in a car park, on public charging stations), which can be done at a local scale, in presence of Renewable Energy Sources;
- **[EV user services]** Design of user-centric information / incentive mechanisms (to share EV charging infrastructure in space and / or time). On this aspect, an interesting research question would be to propose some efficient "rules", or incentives, to set a "good" EV-charging point assignment (when EV arrive at a station, or in advance through an application). Indeed, as soon as EV and charging points are not all symmetric, and local real electrical limits are taken into account, this can largely impact the performance of charging scheduling: if an EV with a maximal charging power of 10kW is plugged at a charging point of 50kW, it may represent a "loss of global efficiency" if other EV can charge at bigger rates; if a maximal power has to be shared in subsets of charging points in a station, it could be preferable to properly assign EV depending on the associated coupling constraints. The question can be thought also in terms of EV-station assignment.

In particular, the following research aspects could be very beneficial for this field:

- coordination/optimisation of charging decisions for a large set of EVs, and with constraints at hierarchical levels (site constraints; distribution and transmission network ones) ;
- the integration of EV battery aging modelling;
- the integration of load-flow based local electricity network constraints/metrics;
- the analysis of the specificity of EV as a "moving" electricity appliance (not always connected to the grid, not always at the same location);
- the proposition of stable, "fair", and "individually rational" (in the sense of game-theory) economic mechanisms to define EV users charging (flexibility) contracts

3.3.2 Routing Problems

The scheduling and routing problem for technician interventions on the electricity distribution networks is difficult and of high interest due to the number of kilometers and mobilized resources (manpower, vehicles and equipment).

This problem can be decomposed into several coordinated stages:

- **Appointment scheduling** :

  Appointments are scheduled incrementally several days ahead to deal with a flow of appointment requests. They are added in technician routings and must fit technician skills. Routing must be feasible, considering routing and intervention duration. The appointment scheduling process decides a day and a time-window for each appointment.

[1] "Flexibility systems" include: at a local scale, participation to the mitigation/resolution of "congestion effects" at the scale of a site (where other electrical consumptions can be present) or in the electricity distribution network (power losses, voltage regulation issues, transformer degradation); at a global scale the aggregated EV charging flexibility can participate to electricity market mechanisms, large-scale regulation systems (e.g., frequency regulation) or included as a "Virtual Power Plant" in the standard unit commitment problem.

- **Operational**:

  The scheduled appointments are re-optimized every day to determine the daily routing of all technicians of a given area, while meeting the demand (list of operation applications, e.g. maintenance of an electric line), and taking into account several criteria (e.g. distances, equipment that have to be loaded in each vehicle at the beginning of the day, necessary qualifications to perform the operations). The time windows of appointments must be unchanged. Technicians in charge of an appointment can be different as long as they have the required skills and as long as the durations of routing and interventions are compatible. Re-optimized routings are completed with cancellable appointments (for example maintenance operations with no customer interaction).

- **Real-Time**: adjusting the routing schedule to the occurrence of unforeseen events (e.g. cancellations and weather).

This problem can be seen as a multiple Vehicle Routing Problem with Time Windows (VRPTW). Current work was conducted on a simplified problem (operational stage only), using local search techniques and mixed integer linear programming.

Further research could focus on the following difficulties:

- Integrating all accurate constraints of operational planning within a strategic planning model, while modelling the evolution of the load;
- Looking at future business needs: routing can be single or multiple i.e. taking into account vehicles with only one technician or several technicians. Multi-modal touring: conventional vehicle, electric vehicle, bicycle and / or walking;
- Multi-site problem: technicians of a given site may take charge of operations that are at the border of neighbouring sites;
- Robust approaches (e.g. to deal with traffic variability) or online optimization for operational planning;
- Dynamic readjustment of the routing schedule;
- Use of previous routings to help build new ones (use of machine learning suggestions to help optimization algorithm).

3.4 Large scale problems

A general characteristic of all the above problems is their large size, and the operational need to solve problems "unreasonably fast", i.e., the constraints on computing time are unreasonable w.r.t. the size of the problem. Most problems dispose of significant structure. Moreover in many operational processes one can encounter the frequent solution of very "similar" instances. Fine-tuned algorithms of parallel computing or hot-starting could, depending on the underlying structure, be of great interest.

3.5 Competition, equilibria

In a dynamic and competitive environment, the organization and management of the electrical system are undergoing profound change due to many factors. These include the development of renewable energies, changes in the use of electricity and consumption patterns, opening up to competition and the end of regulated tariffs. This leads to a major change in the relationship between the various players in the electricity system, which requires reconsidering the design of pricing methods to integrate the behavior of the players (decentralized production, self-consumption, electric vehicle charging), taking into account the competition (or a set of rules for the regulated sector) in order to offer attractive and innovative contracts for the supply of electricity and the offer of services. In addition, smart meters open up interesting prospects in the design of innovative tariffs. One question is therefore how to develop and maintain operational methods of pricing and design of commercial offers in the regulated and competitive areas of the electricity sector.

Competition aspects can also show when various users need to recharge their electric vehicles. In this situation the competitive aspect ties in with queuing theory. One could think of the following situation:

1) A situation wherein the users have to first station their vehicles on a spot without a recharging station and then move their vehicle when a station is freed

2) A situation wherein a recharging station can be connected to several vehicles but only one can be charged at any given time

Altogether an efficient set of rules has to be set up, with respect to the management of the recharging station and the efficiency of handling several electric vehicles. As an example, a FIFO list would mean that all subsequent vehicles would have to wait for recharging, potentially a long time. Whereas if a simultaneous charging strategy is pursued, all vehicles would proportionally wait longer if more vehicles are connected.

3.6 Disciplinary approaches

IROE also has interest in various more disciplinary developments. These developments should nonetheless be tied in with some of the above described problems, but then in a remoter way. The studied developments could leverage, on identified underlying, mathematical structures of the energy management problems and suggest new insights. To give an example, several energy management problems (e.g., unit commitment) can be seen as the minimization of a sum of extended valued functions with mutually independent arguments under some coupling constraints. In similar vein, offering tools for handling uncertainty in various parts of an optimization problem is also useful. The latter could consist of the study of extension of stochastic programming to energy management-like structured problems – for which already a rich literature exists. The possible IROE developments in this class could consist of new theoretical insights into the underlying mathematical structure of the problems at hand or improved / new algorithms. Nonetheless an effort should be made to explain what practical advantages these insights could ultimately have.

3.7 Quantum computing

The last three decades have seen major advances in the field, with the development of a comprehensive theory of quantum information processing, and the specification of "Quantum Turing Machines", together with the complexity classes associated with the problems likely to be solved by these approaches [Deutsch 85] [Bersetin Vaziran 97] [Aaronson 10] [Nielsen, Chuang 10] [Rieffel, Polak 14]. Although no general theory of “quantum speedup” does exist, several dozen of particular quantum algorithms have been discovered, presenting significant speedups (up to exponential) compared to their classical counterparts [Jordan 19] in practice.

In terms of quantum “hardware”, if significant uncertainties remain as to the possibility of building “Universal Quantum Calculators” robust to errors and having a large number of qubits, constant progress has been made for several years. There are already operational achievements of “Quantum Processor Units” (QPU) specialized in tasks for which “quantum advantages” are possibly to be demonstrated, this last point being further the subject of controversy in the scientific community (Google Sycamore processor [Google 19], D-Wave “Quantum Annealers” [D-Wave 21]…)

One speaks of "Noisy Intermediate Scale Quantum Computing" (NISQ) to designate the current state of the art in the field, a period that should last a few more years during which error-prone quantum computing devices with a limited number of qubits available will be usable to speed up specific tasks, being integrated with conventional computing means in hybrid architectures.

At the same time, the dynamics of the field strongly stimulate classical computing itself, many works seeking to push back the limits of which : on the one hand by implementing advanced techniques to effectively simulate QPUs on classical high performance computing architectures (cf. IBM's response to the announcement by Google to have achieved a form of "quantum supremacy" with its Sycamore processor [IBM 19], and on the other hand by proposing classical “Quantum Inspired algorithms” efficiently reproducing on classical machines certain quantum algorithmic approaches (cf. the simulation of "quantum annealing" by Monte-Carlo methods, for hard optimization problem solving [Mazzola, Troyer 17] [Fujitsu 20][Toshiba 20]).

It is of course clear that any “quantum inspired” (e.g., NISQ) optimization approach aiming to tackle any of the previously defined “energy management problems” will need to be properly benchmarked against the existing state of the art approaches. This benchmark should serve, at the very least, to indicate the gap between the state of the art in both fields. It is reasonable at the current state to consider implementations on smaller problems or to think of the quantum approaches as proof of concept.

3.7.1 Quantum approaches for hard optimization

Optimization, and especially combinatorial optimization, is one of the most active fields of research and development in the applications of quantum computing.

There is nothing surprising about this given the fact that the combinatorial optimization problems belong for the great majority of them to complexity classes (NP, NP-Complete and NP-difficult) for which we does not know of an efficient resolution algorithm (polynomial) on classical computers, while certain properties of quantum computers (exponential nature in the number of qubits of the available memory, quantum parallelism, interferences, entanglement) give hope for significant accelerations in the resolution of this type of problems.

The fact remains that in this area, as in all the others, there is no guarantee that the properties specific to the quantum world systematically provide significant speedups compared to the best known classical algorithms.

In practice and until today, only one quantum algorithm provides an exponential speedup on an NP (but unproven NP-Complete) problem: that of Peter Shor [Shor 95] for the factorization of integers. This algorithm caused a stir because the security of the "RSA" encryption keys, which protects the vast majority of communications on the Internet, is based precisely on the difficulty of solving this problem on a conventional machine for large integers.

However, a number of very promising quantum approaches have been developed to attack these combinatorial problems:

- Grover's algorithm [Grover 96] provides a quadratic speedup with respect to an exhaustive enumeration algorithm (always exponential in the worst case), for any problem in NP;
- In the same spirit, recent work is applied to Branch & Bound to accelerate the backtracking phases [Montanaro 20];
- The quantum adiabatic algorithm (Quantum Adiabatic Algorithm QAA) [Fahri et al 00] [Fahri et al 01], derived from a general model of quantum computation [Albash, Lidar 18], can be used for solving problems of combinatorial optimization on “analog” quantum machines, by identifying such a problem in search of a minimal energy state of a Hamiltonian applied to the qubit system;
- Its discrete approximation based on quantum gates, the QAOA algorithm (Quantum Approximate Optimization Algorithm "[Fahri Goldstone 14] [Fahri Goldstone 16], constitutes a hybrid approach for the same type of problems associating a quantum circuit and a classical computer;
- Quantum Annealing, an adiabatic approach limited to certain types of Hamiltonians [Albash, Lidar 18], and therefore to certain types of combinatorial problems, can be seen as the quantum version of simulated annealing, a well-known heuristic technique for non-convex optimization. This approach is the subject of numerous industrial applications, in particular on the machines proposed by the company D-Wave [D-Wave 20] whose contribution in terms of quantum acceleration remains disputed [Troels et al 14].
- Simulated Quantum Annealing, a method based on Monte Carlo simulation of Quantum Annealing originally proposed by [Mazzola, Troyer 17] and concerned to many developments since then. It is a major candidate to deal with these problems in a “quantum inspired” approach, with the great interest of being implementable on classical computers.

Apart from the combinatorial optimization itself, we should also mention the HHL algorithm for solving linear systems [Harrow et al 09]. This polynomial problem on a classical machine and which plays an essential role in many applications is made logarithmic by HHL on a quantum machine, under certain conditions.

3.7.2 Research objectives

All areas of application of difficult optimization, typically combinatorial / discrete, are targeted.

In particular, a very large number of problems stemming from energy management, from the classic unit-commitment to the smart-charging of electric vehicles, including the most diverse scheduling problems (placement of plant shutdowns, optimization of tasks of maintenance inside stops, rounds of intervention vehicles, logistics of telephone call centers, etc.), are likely to benefit from these approaches.

A particular point of interest concerns the consideration of *constraints* in approaches resulting from adiabatic computation (QAA, QAOA, QA, SQA). Indeed, these approaches are based on the modelling of the problems to be solved in forms most often imposing the absence of constraints (typically quadratic binary without constraints, called QUBO for Quadratic Binary Optimization Problem). The effective embedding into these approaches of the constraints present in the vast majority of industrial problems constitutes an important subject of research [Lucas 14] [Glover 18][Ohzeki 20].

More generally speaking, the research carried out at EDF on this topic aims to assess the potential applications of quantum approaches to the problems mentioned above, without expecting at this stage better results than those obtained by the classical approaches currently used for solve them. The objective is to qualify these methods on "NISQ" calculation means for small instances of problems of interest to EDF, and to study their possibility of scaling up in the future.

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